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Do Credit Market Shocks affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and `Normal' Economic Times*

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Abstract

We estimate the effect of the sharp reduction in credit supply following the 2008 financial crisis on the real economy. The identification strategy relies on the substantial heterogeneity in the degree to which banks cut lending over this period. Specifically, we predict changes in county-level small business lending over 2007-2009 by estimating the national change in each bank's lending that is attributable to supply factors (e.g., due to differences in the crisis' effect on their balance sheets) and, subsequently, allocating this quantity to counties based on the banks' pre-crisis market shares. We find that in 2008, 2009, and 2010, this measure is highly predictive of total county-level small business loan originations indicating that, at least in the near term, a firm cannot easily find a new lender if its bank limits access to credit. Additionally, we find that areas with more exposure to banks that cut small business lending during this period experience depressed employment and business formation. Upper bound estimates suggest that the 2007-2009 decline in small business lending accounted for up to 20% of the decline in employment in firms with less than 20 employees, 16% of the total employment loss, and 30% of the decline in inflation adjusted aggregate wages during this period. Finally, we note that the relationship between lending supply and economic activity is not evident in the 1997-2007 period, underscoring the unique circumstances during the Great Recession.

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The financial crisis caused an extraordinarily sharp decline in employment and, despite extensive fiscal and monetary policy interventions, the subsequent recovery has been slow compared to the recovery from typical recessions. The employment to population ratio peaked at 63.3% in early 2007, reached a low of 58.2%, and as of September 2012 had only risen to 58.7%. The range of explanations for this deep decline and slow pace of recovery include reduced aggregate demand (Mian and Sufi 2012), uncertainty (Baker, Bloom, and Davis 2011; Bloom et. al. 2012), and structural factors (Charles, Hurst, and Notowidigdo 2012).

This paper considers the role of declines in bank lending over this period. Small firms, who are more reliant on bank lending, experienced disproportionate employment losses in the Great Recession (Haltiwanger et al. 2011, Krueger and Charnes 2011, CBO 2012). Based on this observation, several commentators (eg. Bernanke 2010, Krueger 2010) have suggested that fractured credit markets could have played a major role in overall employment declines. Indeed, the academic literature dating at least to Brunner and Meltzer (1963) and then revived with new purpose by Bernanke (1983) and others has emphasized that banks can play a central role in the functioning of the economy because small and medium-sized businesses do not have ready substitutes for banks for their credit needs. It is for this reason that banks have been labeled "special" and it is thought that their health can be an important determinant of macroeconomic fluctuations (Bernanke and Gertler 1995; Rosengren Driscoll 2000; Ashcraft 2005).

We employ a new approach to assess the role of the supply of credit from banks to small businesses in affecting the overall economy between 2007 and 2010. This exercise provides an opportunity to gauge the economic consequences of shocks in one segment of the credit market in contributing to the Great Recession, as well as providing new evidence on whether banks are special. A second objective of this paper is to compare the relationship between local lending supply shocks and economic activity between this and the less turbulent 1997-2007 period.

The identification strategy relies on the substantial heterogeneity in changes in national banks' small business lending during the financial crisis and isolating the portion of it due to supply factors (e.g., differences in the crisis' effect on their balance sheets). For example between 2007 and 2009, Citigroup reduced small business lending by 84%, while US Bancorp's small business lending declined by just 3%. Specifically, we predict the change in county-level small business lending over the 2007-9 period with interactions of the banks' pre-crisis county market shares and their national change in lending. Importantly, we purge the measure of their national change in lending of their exposure to local markets to isolate supply, rather than demand, shocks in lending. Further, small bank lending is highly localized (Brevoort, Holmes and Wolken 2009) and there is sufficient variation in banks' market shares across counties in

the same state that the results are based on within-state comparisons. The essence of our approach is to ask whether within a state, counties with more Citigroup branches than US Bancorp branches experienced relative declines in their economies.

There are four primary findings. First, predicted reductions in lending in both 2008 and 2009 are associated with sharp declines in total county-level small business loan originations. For example, a one standard deviation reduction in predicted lending in 2008 and 2009 is associated with a 17% reduction in total county-level small business loan originations in 2009. At least in the near term, it appears that businesses are unable to switch lenders. Second, this same predicted decline in lending depresses 2009 levels of small establishment employment by 0.6 percentage points, small establishments by 0.8 percentage points, and county-level payroll and earnings by 0.65 percentage points. Third, these patterns are not present among establishments that should be insulated from local credit shocks but might benefit from competitors' declines, namely small establishments that are part of large multi-state chains and large establishments. Fourth, the implementation of the identical empirical approach in the 1997-2007 period fails to find a relationship between lending supply and economic activity, underscoring the unique circumstances during the Great Recession.

Was this reduction in supply a major contributor to the employment decline in the last several years? Answering this question requires making assumptions about the share of the national decline in lending that was supply driven, rather than due to demand shifts, and about the relevant general equilibrium effects. In the absence of reliable evidence on these key issues, we calculate an upper bound estimate of the aggregate effects by assuming that the entire 22% and 33% reductions in small business lending in 2008 and 2009, respectively, were due to banks' credit supply decisions.[1] Under this polar assumption, the 2007-9 decline in small business lending led to a 1.4 percentage point decline in employment in firms with less than 20 employees, a 0.8 percentage point reduction in total employment, and a 1.2 percentage point decline in aggregate wages by the end of 2009. As bases of comparison, small business employment, total employment, and inflation adjusted aggregate wages declined by approximately 7, 5, and 4 percentage points, respectively, between 2007 and 2009.

The analysis is conducted with the most comprehensive data ever assembled to investigate the role of bank lending on the real economy. We use Community Reinvestment Act disclosure data to obtain a measure of small business loan originations at the bank by county level on an annual basis. The data on outcomes is derived from several sources. Dun and Bradstreet's NETS database is a proprietary data set that has information for most establishments; its key feature is that it allows for the calculation of county-level growth rates for categories of establishments defined by size and whether they are part of a chain. These data are complemented with data on employment and earnings from the County Business Patterns,

[1] These figures refer to small business loan originations from the Community Reinvestment Act disclosure data.

Quarterly Workforce Indicators, and the Quarterly Census of Employment and Wages, all of which are derived from administrative data.

There is an emerging literature on the effects of post-Lehman credit disruptions on real economic activity that is related to this paper, including Gozzi and Goetz (2010) and Chodorow-Reich (2012).[2] Gozzi and Goetz (2010) find that small banks that were more exposed to liquidity shocks through higher shares of noncore liabilities on their balance sheets during the 2007-9 crisis reduced their lending more than small banks that relied on retail deposits. Further, MSA's with more of these vulnerable small banks experienced deeper employment losses. However, as the authors note, these banks accounted for just 11 percent of total business lending and 25 percent of total bank lending to small businesses. Chodorow-Reich (2012) considers employment decisions of firms who had obtained loans in the syndicated market prior to the crisis. These firms were less likely to obtain a new syndicated loan, and experienced reduced employment growth after 2008 if the lead bank in a previous syndicated deal with the firm was relatively unhealthy post-Lehman. Thus, this paper provides critical evidence on the mechanism on the link between credit supply shocks and employment for one segment of the market. However, it does not directly observe the impact on overall employment, including the role of new business formation and destruction.

This paper contributes to the literatures on the role of banks in the economy in several ways: Our study is nationally representative; it is the first to consider how the employment response to lending shocks changes over time, both during a financial crisis as well as during periods when financial markets were functioning more normally; it focuses on small firms which are more likely to be affected by bank supply decisions; it considers new business formation (and destruction) as well as employment growth of existing businesses; it incorporates the lending decisions of large banks which originate the majority of small business loans; and it utilizes a new research design that allows us to control for confounding demand factors that may have affected employment growth. Our study also contributes to the literature on the causes of the Great Recession and subsequent slow recovery.

The remainder of the paper is organized as follows. Section II provides some background on credit markets, the financial crisis and small businesses. Section III provides details on the data sources. Section IV explains the research design and how it is operationalized. Section V outlines the econometric models and presents the results. Section VI interprets the findings and Section VII concludes.

[2] Also see Duygan-Bump et al. (2010).

II. Background on Credit Markets, the Financial Crisis, and Small Businesses

This section provides background on the effect of the financial crisis on credit markets and the role of small businesses in the U.S. economy. Further, it reviews the evidence on the importance of banks as sources of credit for small businesses.

A. Credit Markets and the Financial Crisis

The mechanisms behind the unraveling of the financial system in 2008 are complex, and analyzed in depth in Brunnermeir (2009) and Shleifer and Vishny (2011) among others. Broadly, the financial crisis of 2008 was precipitated by the collapse in the prices of mortgage-related securities. In the years preceding the crisis many commercial banks built up large portfolios of mortgage-back securities in an attempt to chase higher returns than those offered by other financial assets. The subsequent devaluation of these securities increased the perceived default risk of these institutions and increased their cost of funding. Additionally, as asset values fell, financial institutions were forced to sell assets at fire-sale prices to meet margin calls due to lower collateral values, thus lowering asset prices even further. The decline in asset prices made it increasingly difficult for firms to use these assets as collateral to raise new funds resulting in increased rollover risk. As liquidity became increasingly scarce, credit markets deteriorated, and by August 2007 the market for short-term asset-backed commercial paper had completely dried up. The inability to roll over short-term debt, and elevated withdrawals of demand deposits and capital redemptions stressed financial institutions, and led a number of them, including Lehman Brothers at the peak of the crisis in September 2008, to fail.

The extent of the crisis on liquidity and credit markets can be seen in several aggregate indicators. The TED spread, which is the difference between the interest rates on three month interbank loans and three month U.S. treasury bills (which are treated as riskless), is widely considered a measure of liquidity in the financial market because it reflects banks' confidence about the risk of default by their counterparties. Figure 1 documents the monthly average TED spread over the 1989-2012 period. The spread was generally less than 100 basis points and below 50 basis points for most of this period, but beginning in August 2007, and continuing through the remainder of the year, it became elevated varying between 125 and 200 basis points over increasing concerns about banks' exposure to subprime mortgages. As the extent of the financial crisis emerged and Lehman failed, the TED spread jumped to unprecedented levels, reaching 340 basis points on October 10, 2008. The TED spread returned to its historical levels by the middle of 2009 during a period where governments around the world intervened into capital markets and more clarity about banks' financial health arrived.

Numerous indicators suggest that this liquidity crisis translated into less available credit across the economy. According to data from the Federal Reserve Survey of Senior Loan Officers (Figure 2), in the first quarter of 2009 the net percentage of loan officers tightening standards for medium and large firms was 64 percent as compared to zero percent in the first quarter of 2007. A similar pattern is seen in the National Federation of Independent Business survey of its members: loan availability began to decline in the beginning of 2007 and did not reach its nadir until 2009 and has been on a slow recovery since then (Dunkelberg and Wad 2012). Commercial bank lending fell considerably over this period, especially to small businesses. Figure 3 shows constant dollar annual loan balances broken down by loan size from the FDIC Call Reports, relative to 2007. Total balances for loans under $1 million fell by about 5% between 2007 and 2010 while loans greater than $1 million were flat.[3]

Important patterns are evident in the small business lending data that are the focus of this paper. Figure 4 plots the log of constant dollar loan originations to small businesses—defined here as businesses with gross revenues of less than $1 million—from banks reporting under the Community Reinvestment Act.[4] It is apparent that the financial crisis of 2008 led to an enormous decline in originations to small businesses, declining by 52% between 2007 and 2010. Figure 5 is a kernel density plot of the change in log (nominal) originations between 2007 and 2009 across counties, weighted by the number of establishments in the county in 2006. It reveals the substantial geographic dispersion in the decline in lending. The pervasive nature of the recession is evident in the fact that almost all establishments were in counties where lending declined.

A number of papers document this decline in lending and explore empirically the underlying mechanisms. A common thread is that this decline was in large part "supply-driven." Ivashina and Scharfstein (2010) document that new loans to large borrowers fell by 79% between the second quarter of 2007 and the fourth quarter of 2008. They argue that an important mechanism behind this decline was banks' reduced access to short-term debt following the failure of Lehman, coupled with a draw-down of credit lines by their borrowers. Combined, these two effects reduced liquidity and led banks to cut new lending. Using Community Reinvestment Act data, Huang and Stephens (2011) show that multi-market banks' exposure to markets with housing busts affected the supply of small business loans within all MSAs. A similar conclusion is reached by Berrospide et al. (2011). Gozzi and Goetz (2010) find evidence that differences in liability structure of small U.S. commercial banks, particularly the use of "non-core" financing, affected lending patterns during the 2008 crisis. Almeida et al. (2012)

[3] As noted by Ivashina and Scharfstein (2010), loan balances are a stock measure reflecting both changes in loan originations and repayment schedules. The initial increase in loan balances for larger borrowers is consistent with borrowers reducing repayments in order to maintain more cash as a precautionary measure following the collapse of Lehman.

[4] Small business loans reported under the CRA are of $1 million or less.

document that firms with a higher fraction of debt maturing around the onset of the panic of August 2007 had lower credit quality, which could arise from an inability to rollover debt due to frozen credit markets.

In sum, this subsection has demonstrated that there was a sharp contraction in the supply of credit across the economy during the Great Recession. Indeed, the extent of illiquidity and credit restrictions were unprecedented over the periods covered by these data series. For the purposes of our analysis, which relies on annual data, we will treat 2008 and 2009 as the years when the supply of credit decreased (noting that in practice this probably began in the second half of 2008).

B. A Primer on the Role of Small Businesses in the U.S. Economy

In 2007 firms with less than 100 employees represented approximately 36% of employment and 20% of net job creation.[5] There is considerable debate about the importance of small firms for net job creation. For example, using different datasets on firm employment dynamics Neumark, Wall and Zhang (2009) and Haltiwanger, Jarmin, and Miranda (2011) both find evidence supporting an inverse relationship between net growth rates and firm size, but the latter study notes that it is really new businesses rather than small businesses that disproportionately contribute to net job creation. Several studies have documented the anemic performance of small firms during the Great Recession and subsequent recovery. Using an experimental version of the Bureau of Labor Statistics JOLTS series, Krueger and Charnes (2011) find that small establishments experienced larger employment declines in the early stages of the recession, and exhibited slower growth after July-2009. Similar patterns are documented by CBO (2012) and Haltiwanger et al. (2011). According to BDS data, firms with less than 100 employees had a net job creation rate of -0.7% in 2008 and -6.8% 2009.

C. The Central Role of Local Banks in Supplying Credit for Small Businesses

It has long been recognized that banks have an important role in mitigating frictions in credit markets. It has been theorized that asymmetric information prevents capital from flowing to firms with profitable investment opportunities (Stiglitz and Weiss 1981) and that financial intermediaries can lessen the effects of these market failures, particularly for small firms. The empirical literature on this topic has found evidence that commercial banks are able to obtain "soft" information on firms that helps on the credit decision but is not necessarily transferable (eg. Agarwal and Hauswald 2010).

Indirect evidence of the role of banks in reducing informational asymmetries includes the highly localized nature of small business lending and lending relationships. For example, using data from the Survey of Small Business Finances through 2003, Brevoort, Holmes and Wolken (2009)

[5] Calculated using Business Dynamic Statistics.

estimate the median distance between firms and their suppliers of credit was 3 miles and only 14.5 percent of small firms borrowed from an institution that was more than 30 miles from their headquarters.[6] There are a number of empirical studies that have investigated the benefits of long-term lending relationships as a way to overcome information asymmetries in the lending market (see for example, Cole 1998, Berger and Udell 1995, Hoshi, and Petersen and Rajan 1994). Berger et. al. (2002) argue that firms that borrow from large banks tend to be more credit rationed suggesting that firms that are cut off from credit from larger banks (as in our study) may not be able to obtain credit elsewhere. In the macroeconomics literature, credit market frictions have been suggested as a channel for the transmission of monetary policy, specifically through the effect of interest rates on the external finance premium, which arises through imperfections in credit markets (Bernanke and Gertler 1995).

III. Data Sources

The predicted lending shock described above is constructed using Community Reinvestment Act (CRA) disclosure data from the Federal Financial Institutions Examination Council (FFIEC). The CRA requires banks above a certain asset threshold to report small business lending each year and by Census tract. The asset threshold was $1.033 billion in 2007 and is adjusted with CPI.[7] We estimate that in 2007 CRA eligible banks accounted for approximately 86% of all loans under $1 million.[8,9]

FFIEC provides data by bank, county, and year. There are two definitions of small business lending that are made publicly available: the total dollar amount of small business loan originations, defined as loans under $1 million (≈30% of total originations in 2007), and the dollar amount of small business loan originations to businesses with $1 million in annual gross

[6] Using data from a single large commercial bank, Agarwal and Hauswald (2010) find a similar median distance between the lending branch and the firm (2.6 miles). They argue that proximity helps banks acquire valuable "soft" information through interviews. Using data from the Community Reinvestment Act, Laderman (2008) finds that only about 10 percent of small business lending is from banks with no branch in the local market.

[7] Before 2005 the asset threshold was $250 million.

[8] We use FDIC Call report data from 2007 to compute the fraction of all loan balances held by banks below the asset threshold. This is an inexact estimate because loan balances in the FDIC Call reports are a stock measure while CRA originations are a flow.

[9] FDIC Call reports are not designed to study regional lending because the balance sheet data are only available nationally at the bank-level, but for small community banks it may not be a bad approximation to assign the location of the bank' headquarters as the market in which the bank lends (something that would clearly not work for, say, Bank of America). In Section IV we use these data to better understand the implications of excluding the smaller banks that do not meet CRA reporting thresholds from our analysis. We find no evidence that small banks change lending balances in response to lending shocks of larger banks and we conclude that our analysis is not greatly affected by the exclusion of these smaller banks.

revenue or less (≈13% of total originations in 2007).[10] Because our focus is on small firms, we use the second measure. These data are available from 1997 through 2010.

To calculate changes in a bank lending over time without including changes due to acquisitions, we employ the standard correction (eg. Bernanke 1991), which is to identify acquisitions over every pair of years and treat the acquired and acquiring bank as a single entity over that span. Following this procedure, we roll-up banks to the holding company level.[11] This leaves us with 654 bank holding companies that are in our data for at least one year over the 1997-2010 span. While these are a relatively small fraction of all banks, they are the largest banks nationally and thus account for a large share of all lending.

Outcome variables are constructed from the National Establishment Time-Series (NETS) database, County Business Patterns (CBP), Quarterly Workforce Indicators (QWI), and the Quarterly Census of Employment and Wages (QCEW). The CBP, QWI, and QCEW datasets are derived from administrative data and contain county-level information on employment and earnings. The CBP are derived from the Census Business Registrar while the QCEW and QWI are derived from state unemployment insurance records.[12] Because the CBP and QCEW have very limited information on firm size we use them exclusively for county-level analyses.[13]

To study small firm dynamics we arranged for a special extract of the National Establishment Time-Series (NETS) database. The NETS database is compiled by Walls and Associates using Dun and Bradstreet's Market Identifier files.[14] From the establishment micro data we are able to construct a county-level time-series of job creation, job destruction, firm entry and firm exits by establishment size and also broken down by whether the establishment is a standalone firm or whether it is part of a chain.

A key advantage of the NETS micro data is that we can compute growth rates during a period, based on establishments' sizes at the beginning of that period.[15] Specifically, for a given size category *k* (e.g., establishments with less than 20 employees), we define employment growth between *t-1* and *t* for size category *k* in a county as:

[10] In the FDIC Call reports, loan balances of $1 million or less are approximately 30% of all loans.

[11] We used the FDIC institution directory to identify acquisitions, and the FIDC Call reports to link banks to their holding companies.

[12] The QCEW is produced by the Bureau of Labor Statistics and the QWI by the Census.

[13] The County Business Patterns has information on the number of establishments by size-category of firm, but this breakdown is inadequate for our purposes. The QCEW does not breakdown the data by firm size.

[14] See Walls (2007) for an in-depth description of these data.

[15] An example may help to clarify this approach to calculating the growth rate. Consider the calculation of the growth rates of establishments with 20 or fewer employees and 21 to 150 employees. Now, suppose that in 2007 an establishment had 100 employees and in 2008 it shrunk to 10 employees and then increased to 15 in 2009. This establishment would contribute to the 2007-8 growth rate for the 21 to 150 employee category and to the 2008-9 growth rate for the 20 or fewer category. .

(1) Employment growth rate$_{t,k}$= [jobs created by new establishments$_{t,k}$-jobs lost from closing establishments$_{t,k}$+employment in establishments$_{t,k}$ - employment in establishments$_{t-1,k}$ +in-migration$_{t,k}$-out-migration$_{t,k}$]/employment$_{t-1,k}$

In this expression, *employment in establishments$_{t,k}$* is year *t* employment of establishments in category *k* in *t-1, jobs lost from closing establishments$_{t,k}$* is *t-1* employment of establishments which closed between *t-1* and *t, in-migration$_{t,k}$* refers to year *t* employment of establishments in category *k* in year *t* that were in a different county in year *t-1*, while *out-migration$_{t,k}$* measures year *t-1* employment of establishments that were in the county in year *t-1* and then moved. Similarly, we compute the establishment growth rate as:

(2) Establishment growth rate$_{t,k}$= (new establishments$_{t,k}$-closing establishments$_{t,k}$+establishments that moved in$_{t,k}$-establishments that moved out$_{t,k}$) /establishments$_{t-1,k}$

To assess robustness we also present estimates using a new `beta' version of the QWI that decomposes county employment by firm size.[16] These data are missing several states, including California, and we will define growth rates crudely as the difference in employment across years. Because of these shortcomings these data are not be the focus of our paper. Nevertheless, they do show a similar pattern of estimates as the NETS data.

There is some debate about the quality of the NETS data. For example, Neumark et al. (2011) argue that the NETS database is sufficiently high quality to study small business dynamics while Haltiwanger et al. (2011) raise some questions about the coverage of the database and its ability to pick-up startups. Appendix Figure 1 plots the employment growth rate across these datasets. While there are some differences, business cycle fluctuations are of a similar magnitude.[17] Because our focus is on small businesses, Panel C of Appendix Table 2 compares employment growth rates of small establishments at the state and year level between the NETS data and the Census Business Dynamics Statistics (BDS).[18] The correlation between these rates across counties is 0.72 for the 2005-2009, which seems reasonably high. We conclude that

[16] These data are available at the Cornell University Social Science Gateway and were made available to us by Lars Vilhuber. The Social Science Gateway is funded by NSF grant 0922005 and John Abowd and Lars Vilhuber are the Principal Investigators.

[17] In Appendix Table 2 we compare year-over-year log changes in county total private sector employment in the NETS to CBP, QWI, and QCEW. Surprisingly, the correlation in log changes in employment between the administrative datasets are only in the 0.6-0.7 range *after* weighting by the number of establishments in the county in 2006. The QWI and QCEW correlation of 0.7 is especially noteworthy because both of these datasets are derived from unemployment insurance records suggesting that statistical agency processing (for QWI the Census and for QCEW the BLS) matters quite a bit. The NETS correlations with the administrative data are in the 0.4-0.5 range, which are not especially high, but not too far from the correlation we observe between the administrative datasets. This lower correlation may be because of measurement error, but it could also arise because the NETS database covers establishments that are not included in the other datasets including non-employers.

[18] State is the smallest geographic unit provided in the BDS data.

there is sufficient signal in the NETS data to study annual employment dynamics at the county-level.

For all of the employed datasets, we exclude observations where data has been suppressed. Additionally, we exclude counties for which there is at least one missing value between 1998-2010 (2009 in the case of NETS) in order to preserve a balanced panel. These selection rules amount to dropping only a very small number of counties.[19]

Finally, we note the use of two additional sources of data. In the main estimating equations, we also include county characteristic controls derived from Census data and the QCEW.

IV. Research Design

A. Isolating Supply Shocks in Lending

This paper's research design is based on the observation that some banks cut small business lending more than others, and that bank market shares vary across local areas. Table 1 shows the percent change in the nominal dollar amount of small business lending between 2007 and 2009 as reported to the Federal Financial Institutions Examination Council (FFIEC) under the Community Reinvestment Act.[20] Over this period, small business lending declined by 48%, and the median bank in our sample reduced small business lending by 32%.

However, underlying these national trends there is considerable heterogeneity across banks. The table presents the percent change economy wide and for the 13 largest banks that have CRA loans (as measured by total assets in 2007). Bank of New York Mellon, JP Morgan Chase, Citigroup, and Bank of America all reduced their new loans to small business by more than 75%, while the decline was less than 35% for Wells Fargo, HSBC, BB&T, PNC Financial, and US Bancorp.

Our identification strategy exploits the heterogeneity in counties' exposure to these banks, under the testable assumption that firms can only incompletely substitute for the reduction in the supply of credit from their bank. Although we will test this assumption empirically, evidence of frictions in this market is documented in the numerous papers cited above. Based on this literature, we believe that it is plausible that a lending supply shock to a subset of banks in a region can affect aggregate lending in that area since firms cannot easily substitute across banks. This hypothesis will be tested directly in the first stage of estimation.

[19] We do not balance the QWI panel because there are too many missing values as a result of staggered entry of states into the sample.

[20] As before, small business lending is defined as loans to firms with $1m gross revenues or less.

One of this paper's innovations is the development of a modified version of the shift-share approach that has been used to identify local labor demand shocks as in Bartik (1991).[21] A standard application of the shift-share approach to our setting would involve the construction of an instrument for bank lending in county *i* and year *t* as the sum across all banks in *i* of the interaction of bank market shares in *t-1* and changes in lending of those banks nationally between *t-1* and *t*. The identifying assumption from this standard approach is that the shocks to aggregate bank holding company lending are supply shocks, rather than reflecting demand conditions in the areas where the banks operate. However, this assumption is likely to be invalid in this setting where banks' balance sheets are a function of the local demand shock in the counties where their branches are located.

We develop a modified shift share approach to solve this problem of identification. The presence of branches of multiple bank holding companies in each county provides an opportunity to purge the common county or demand effects from the banks' national changes in lending. Specifically, we estimate the following equation that attempts to divide the contribution of demand and supply to bank lending:

$$\Delta \ln (Q_{ij}) = d_i + s_j + e_{ij}, \quad (3)$$

where the outcome variable is the percentage change in small business lending by bank *j* in county *i* between two years.[22] We weight the sample by each bank's lending in the county in the base period so that an observation's influence is proportional to its lending in this year. The bank fixed-effects are re-centered so that the (bank asset size weighted) mean of the fixed effects is zero. The vector d_i is a full set of county fixed effects that capture the variation in the change in lending due to the condition of the local economy, which we interpret as measuring local demand.

The parameters of interest are those associated with the vector of bank fixed effects, s_j. They are estimates of banks' supply response that are purged of banks' differential exposure to regional variation in demand for small business loans. The estimated s_j's are estimated for every pair of years beginning in 1997 and between 2007 and 2009 to facilitate the below graphical analysis.

Our modified shift-share approach uses these estimated bank-specific supply shocks (i.e., the , s_j's) to construct a measure of the predicted lending supply shock. For each county and year,

[21] See also Blanchard and Katz (1992), Card (2001), Autor and Duggan (2003), and Notowidigdo (2011), for other applications of this approach.

[22] Small business loan originations are defined throughout as loans to businesses with less than $1m in gross revenues.

the predicted lending shock is computed by taking the weighted average of the bank-fixed effects from (3) for the relevant year, weighting by the bank's market share in the county[23]:

$$p_i = \sum_j m_{ij} s_j, \tag{4}$$

where s_j is the bank fixed-effect from equation (3) and m_{ij} is bank *j*'s CRA small business loan market share in county *i*. We standardize the county-level predicted shock variable using the mean and standard deviation of p_i weighting by county-level lending in the base year. In addition to computing the predicted lending shock across pairs of years, we calculate this measure over 2007-2009.

The power of this approach is that the identifying assumption is weaker than in the standard shift-share approach. Specifically, the identifying assumption now requires that banks with above or below average supply-shifters do not systematically sort into counties with worse than average shocks to outcomes. This assumption will be invalid if, for example, managerial skill in choosing branch locations is correlated with skill in choosing investments for the bank's portfolios.

The second way that we attempt to confront the possibility of confounders is to exploit establishment's differential dependence on bank credit. We compare employment for establishments that are vulnerable to local credit shocks to those who should not be directly affected in the same area. Specifically, we contrast the response of small stand-alone firms that plausibly depend on credit supplied from their local geographic area banks with (non-franchise) establishments that are part of larger multi-state firms, which should not be.[24] Similarly, we compare smaller firms to larger firms who plausibly have more access to alternative sources of financing. Looking at the dynamics of firms who are not directly affected by the lending shock is a useful check of whether our specification is adequately controlling for confounding factors, which should affect both sets of firms. Of course, there may be indirect effects of local lending shocks on firms who are not reliant on local banks. This could be because they can take market share from the firms who are affected or because there is a multiplier from the shock that negatively affects all firms in the area. Such indirect effects would complicate the interpretation of these intra-county comparisons.

B. Empirical Background on the Lending Supply Shock

This subsection provides an empirical summary of the predicted supply shock variable during the key period of the Great Recession. Figure 6 is a map of the United States with counties' shading reflecting which quartile their value of the predicted lending shock variable falls into

[23] To calculate year t's value of the instrument, the estimated bank fixed effects are obtained from fitting equation (3) for changes in bank lending between t and t-1. The relevant bank market share is taken from year t-1.
[24] Multistate firms are defined here as those operating in at least three states.

over the 2007-2009 period. The regional correlation in the values of the supply shock measure is evident, although not always in obvious ways. For example, Florida and Massachusetts appeared to have experienced worse than average shocks while Georgia and Tennessee fared better.

It is also apparent that there is substantial within state variation in the value of the predicted shock, allowing for within state comparisons. It is noteworthy that there is intra-state variation even in Nevada, Arizona, Michigan, and California where the recession was especially severe, reflecting the national character of many banks. The within-state variation in this measure can be seen more clearly in Figure 7 which focuses on Texas.

In Table 2 we show summary statistics on county characteristics depending on whether the county is above or below median in terms of the predicted lending shock for the 2007-2009 period. Columns (1) and (2) are the raw means with no adjustments and column (4) is the within state difference after purging out state fixed-effects. Columns (3) and (5) report the p-values from tests that the covariates are balanced.

Not surprisingly, given the spatial patterns seen in Figure 6, counties with worse predicted lending shocks (below median) have different characteristics than counties with better-predicted shocks. Counties with worse shocks had higher wage growth, home price appreciation, and small business lending growth over the 2002-2006 period, as well as lower 2006 manufacturing share, density and population. These findings accord with Laderman and Reid (2010) who find that tracts that boomed in the 2000's experienced a larger decline in small business lending during the financial crisis.

When looking within states, counties with above and below median predicted shocks look much more similar. Column (4) of Table 2 presents the coefficient of the dummy variable for whether the county is above median in the predicted credit shock in a regression with state fixed-effects. The only characteristics for which there is a significant difference are population and population density. Consequently, in the main analysis we will emphasize specifications that include state fixed-effects and that control for county population, as well as a larger set of county characteristics.

It is also informative to assess whether unhealthy banks systematically sort into particular types of counties. The presence of such sorting might indicate that banks are able to observe something about a county's future prospects that are unrelated to the predicted supply shocks and unobservable to the econometrician. Evidence of such sorting would undermine the validity of our research design.

Table 3 assesses the degree to which unhealthy banks non-randomly sorted into certain counties. In column (1) we regress the fixed-effect of the bank with the largest market share

against the fixed-effect of the bank with the second largest market-share. We do not find a significant correlation between the two. In column (2) we take a more systematic approach by regressing bank *j*'s fixed-effect against the average fixed-effect of other banks in markets where *j* operates, weighted by *j*'s county lending. This specification also shows no significant relationship between the lending change of a bank and the lending changes of other banks in the same market. These spatial patterns are consistent with the presence of unhealthy banks in counties being "the luck of the draw" rather than a systematic sorting of banks into certain counties as a function of their lending policy over 2007-2009.

V. Econometric Models and Results

A. Estimates of the Relationship Between Predicted County Credit Supply Shocks and Loan Originations During the Great Recession

It is not *ex ante* obvious that our measure of predicted lending shocks is predictive of loan originations in the aggregate. If firms who were borrowing from a bank that reduced lending could easily switch to banks that did not reduce lending, then the presence of an unhealthy bank may not have affected aggregate lending in an area. This hypothesis is testable, and is the starting point of the analysis.

For the graphical analysis, we begin by dividing counties according to their credit supply shock value calculated between 2007 and 2009 into the top quartile, middle 50%, and bottom quartile, where the bottom quartile experienced the largest negative supply shock. This coarser illustration more readily lends itself to a graphical analysis. Specifically, we estimate the following model:

$$(5)\ \ln(l_{it}) = p_{i,<25} + p_{i,>75} + \phi_{t,<25}(v_t p_{i,<25}) + \phi_{t,25-75}(v_t p_{i,25-75}) + \phi_{t,>75}(v_t p_{i,>75}) + \varepsilon_{it},$$

where l_{it} denotes small business loan originations in county *i* and year *t*, v_t are year dummies for all years besides 2007, $p_{i,<25}$ is an indicator for whether the county is below the 25th percentile in the supply-shock measure over the 2007-2009 period, $p_{i,25-75}$ is an indicator for whether the county is greater or equal to the 25th and below the 75th percentile, and $p_{i,>75}$ is an indicator for whether the county is equal or greater than the 75th percentile. We weight the sample by each county's establishment count in 2006.[25]

[25] Unless otherwise specified, all models are weighted by the county's 2006 establishment count. We choose this weight because we are ultimately interested in the population of establishments nationally. The first stage estimates are unaffected by weighting, though the reduced form estimates are larger in the weighted models than unweighted models, and the standard errors are uniformly closer to zero. These differences in magnitudes may be due to heterogeneity in the effect size depending on county size, with establishments in larger counties exhibiting a larger response to credit shocks, or they could be due to noise. These differences notwithstanding, we believe

The coefficients of interest are $\phi_{t,25}$, $\phi_{t,50}$, and $\phi_{t,75}$. They report the annual means of small business loan originations for each group, relative to the 2007 value that is constrained to be equal across all groups. This specification allows for a visual examination of whether there are pre- and post -Great Recession differences in trends between the groups of counties.

It is worth noting that the use of loan originations as the dependent variable is similar in spirit to using changes in total loans outstanding as an outcome variable and, in this respect, because the outcome is a flow variable the subsequent models are interpretable as first-differences. Thus, these are relatively rich models where the covariates predict changes, rather than levels of the outcome variable.

Figure 8a plots these coefficients. It shows that small business loan originations fell for all three groups of counties in 2008 and 2009, but the drop was far more pronounced for the counties in the middle quartiles and the bottom quartile for the predicted 2007-2009 shock. The decline in originations continued in 2010, but the relative gap between these groups stabilized. The figure also shows that the bottom quartile and middle quartiles counties had more rapid growth in loan originations relative to the top quartile counties in the years preceding the financial crisis, consistent with the findings in Table 2.

Figure 8b is the regression-adjusted version of Figure 8a and is based on the estimation of:

$$(6)\ \ln(l_{it}) = \delta_{st} + \beta_t X_{it} + \tau_{t,<25}(\xi_t p_{i,<25}) + \tau_{t,25-75}(\xi_t p_{i,25-75}) + \varepsilon_{it}\ ,$$

where l_{it} again denotes small business loan originations in county *i* and year *t*. The model includes a full set of state by year indicators, δ_{st}, 2006 county characteristics (including population and population density) whose effects are allowed to vary by year, and the interaction of a full set of year dummies, ξ_t, with indicators for the bottom quartile and middle quartiles counties.[26] Thus, the comparisons between the groups of counties are made within state for each year.

The coefficients of interest are $\tau_{t,<25}$ and $\tau_{t,25-75}$ that capture the annual within-state differences in loan originations between the counties with top quartile values of the predicted credit supply shock variable with the counties in the bottom and middle two quartiles, respectively. The line with triangle data points plots the coefficients associated with bottom quartile and year interactions (i.e., $\tau_{t,<25}$) and the line with square data points plots the coefficients from the middle-quartiles and year interactions (i.e., $\tau_{t,25-75}$).

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that in this context it would be odd to give substantially less weight to establishments in, say, California than in North Dakota.

[26] The controls are log per capita income, construction share, manufacturing share, log population, and log population density.

The figure confirms that there is a strong first-stage relationship even after these regression-adjustments. Although there are differences in the levels of loan originations between the three groups, the regression adjustment, particularly the state fixed effects and population controls, removes most of the difference in pre-existing trends between them during the years 1998-2007 (and especially 2000-2007).

In the subsequent analysis, we primarily rely on a continuous version of the predicted shock measure. In these models, we focus on the 2008 and 2009 shocks separately and estimate versions of the following model:

$$(7) \quad \ln(l_{it}) = \delta_{st} + \beta X_{it} + \gamma_8 p_{i2008} + \gamma_9 p_{i2009} + \theta_{8,8} 1(t = 2008) p_{i2008}$$
$$+\theta_{8,9} 1(t = 2009) p_{i2008} + \theta_{8,10} 1(t = 2010) p_{i2008}$$
$$+\theta_{9,9} 1(t = 2009) p_{i2009} + \theta_{9,10} 1(t = 2010) p_{i2009} + \varepsilon_{it},$$

where p_τ is the predicted lending shock in year τ. The predicted shock main effects control for differences in annual loan originations as a function of the county-level predicted supply shocks in 2008 and 2009.[27] For ease of interpretation, the p_τ's are standardized to have a mean of zero and standard deviation of 1. We report standard errors clustered at the county level to account for serial correlation.[28]

The parameters of interest are the $\theta's$. They are the coefficients on the interactions of the predicted 2008 credit supply shock with year indicators for 2008, 2009, and 2010 and the predicted 2009 credit supply shock with year indicators for 2009 and 2010. These interactions measure the impact of the shocks on loan originations in the year of the relevant shock and all subsequent years, relative to the rate of loan originations in the years before the relevant shock. Thus, this is a difference in differences-style estimator.

Table 4 reports the θ parameters, as well as some linear combinations of the coefficients that are useful for summarizing the magnitudes. One natural summary is the total effect of the predicted credit shocks during each of the years after the Great Recession began. This will allow for the determination of the actual loss in lending in a given year across counties due to differences in their predicted credit supply shocks. Consequently, we define φ_8, φ_9, and φ_{10} as the effects in 2008, 2009, and 2010, respectively, of a county having a 1 standard deviation increase in the 2008 and 2009 predicted lending supply shocks:

[27] We have also estimated models that include county fixed-effects, which is another way to control for differences in annual loan originations across counties. This alternative approach produced almost identical results. Due to the strong similarity of the results, we emphasize the more parsimonious specification going forward.

[28] We have also experimented with clustering by state but this did not have a notable effect on the standard errors.

$\varphi_8 = \theta_{8,8,}$

$\varphi_9 = \theta_{8,9} + \theta_{9,9}$,

$\varphi_{10} = \theta_{8,10} + \theta_{9,10}$.[29]

For example, φ_9 is the effect on 2009 log loan originations of a county that is +1 standard deviation in the 2008 and 2009 distributions of predicted supply shocks.[30] The effect is composed of both the immediate effect of the 2009 supply shock and the persistent effect of the 2008 shock.

An alternative summary measure is the cumulative effect on lending in 2009 and 2010 for a county that has a 1 standard deviation increase in the 2008 and 2009 predicted supply shocks:

$\pi_9 = \theta_{8,8} + \theta_{8,9} + \theta_{9,9}$,

$\pi_{10} = \theta_{8,8} + \theta_{8,9} + \theta_{8,10} + \theta_{9,9} + \theta_{9,10}$.

Thus, the π's report the total impact on the 2009 and 2010 levels of lending, respectively, for counties that have a 1 standard deviation increase in both predicted lending shocks variables. For example, π_{10} reports how much higher 2010 lending is in counties with +1 standard deviation shocks in 2008 and 2009, compared to counties that had mean values of both of the predicted lending shock variables; it is the sum of the immediate and lagged effects of the shocks.[31]

The models in Table 4 confirm a robust and statistically significant relationship between the predicted supply shock measure and loan originations in 2008, 2009, and 2010. For example in the more robust column (2) specification, the point estimates imply that a county with a 1 standard deviation decline in predicted lending in 2008 experiences a large and persistent decline in loan originations of approximately -7.3% in 2008, -8.4% in 2009, and -8.8% in 2010.[32] The estimate of φ_9 suggests that a county with a 1 standard deviation decline in the supply shock measure in both 2008 and 2009 is predicted to have a 17% reduction in loan originations in 2009 relative to pre-crisis levels, as compared to the mean county. This relationship is highly significant with a t-statistic of about 17. Overall, these estimates provide evidence that there are important frictions in the small business lending market. When firms lose access to credit

[29] The 2009 credit supply shock is assumed to have zero impact in 2008.

[30] Five percent of counties were at least -1 standard deviation in the predicted lending shock in both 2008 and 2009.

[31] As long as the θ's are relatively small, then the π's report the relative percentage reduction in the level of loan originations in 2009 and 2010. For sufficiently large changes in the outcomes, the sum of the individuals θ's does not reflect this full effect because the bases for the percentage changes differ.

[32] More precisely, these are log points.

from their banks, they do not (or are unable to) switch to other banks immediately, thus aggregate lending in the area declines.[33,34,35]

B. Estimates of the Relationship Between Predicted County Credit Supply Shocks and Economic Activity During the Great Recession

Having established a strong relationship between predicted and actual loan originations, we turn to examining the effects of these predicted shocks on measures of economic activity using the same specifications. Before describing these results, we note that the dependent variables are all measured in growth rates or ln differences. Thus, the controls in the statistical models can be interpreted as controls for growth rates. This is not a change in focus from the previous subsection because loan originations are an approximation to the preferred, but unobserved, outcome of changes in the outstanding value of loans to small businesses.

1. Small Standalone Firms. Figures 9a and 9b are constructed identically to 8a and 8b, except the outcome variable is the employment growth rate for small standalone firms, defined as single unit establishments with fewer than 20 employees. The growth rates are calculated according to equation (1) and the plots are based on the estimation of equations (5) and (6), respectively.

Figure 9a reveals that annual employment growth was roughly constant across the three categories of counties from 1998 through 2008. They also reveal a sharp decline in overall employment in 2009. The employment decline is largest in the counties in the bottom quartile in terms of the predicted credit supply shock and smallest in the top quartiles counties.

Figure 9b presents the adjusted version. The line with triangles corresponds to the bottom quartile counties and the squares correspond to the 25-75 counties. A point on the chart represents employment growth in a particular year relative to the top quartile group. The 25-75 group shows an almost identical growth rate in the pre-2008 years as the top quartile group.

[33] In Appendix Table 1 we use FDIC Call Report data to test whether non-CRA banks are offsetting the effects of lower lending from the larger banks. For small banks, defined as those that are not subject to CRA disclosure, we assign banks to the county where they are headquartered. We then estimate whether loan balances of small banks are affected by the predicted lending supply shocks of larger banks in that county. We find no evidence that small banks change lending balances in response to lending shocks of larger banks. Thus, the omission of small banks from the analysis are likely not a major problem for our analysis.

[34] They may still borrow from non-bank sources, this possibility is plausible and of considerable interest. We discuss this in Section V. C.

[35] Appendix Table 3 presents estimates on the interaction of the quartiles (defined using the 2007-2009 predicted shock) with 2008, 2009, and 2010 dummies. These models correspond to the specifications in the graphical analysis. Both specifications tell the same story, with the column (2) specification indicating relative declines in lending of 30% in 2010, 35% in 2009 and 15% in 2008 for the bottom quartile. The analogous effects are 17% in 2010, 21% in 2009 and 12% in 2008 for the interquartile counties. All of these estimates would easily be judged to be highly statistically significant by conventional criteria.

The bottom quartile growth rate is lower, but also somewhat noisy. As in Figure 9a, the largest drop in employment after 2007 is in the bottom quartile group, followed by the middle-50. Regression adjustment results in somewhat smaller changes than the unadjusted version, but the overall pattern is similar.[36]

Panel A of Table 5 allows for more precise statements about magnitudes and statistical significance of the employment growth rate effects for small standalone firms. We estimate equation (7) with two modifications: the dependent variable is either the employment or establishment growth rate for small standalones and we only use data through 2009, which is the last year available in the NETS database at the time of writing. Since the outcome variables are growth rates, it is appropriate to sum the parameters to calculate the total effect of shocks in 2008 and 2009, as well as the cumulative effect in 2009. Column (1) reports estimates from the unadjusted specification, while column (2) presents estimates from the specification that controls for state by year fixed effects and the interaction of 2006 values of county covariates and the year indicators.

The column (1) results shows a sizable and highly significant positive relationship between predicted supply shocks and small business employment growth in 2009, but a negative relationship in 2008. The cumulative effect in 2009 suggests that being -1 standard deviation in the supply shock distribution in 2008 and 2009 is associated with -0.6% lower employment growth over the 2008-2009 period. However, this specification is comparing areas that are far-removed from each other. Since different regions of the country were likely differentially affected by the economic downturn for a variety of reasons that are not directly related to bank lending supply, such as exposure to the construction or manufacturing sectors, a richer model that controls for regional effects is desirable.

The more robust column (2) results in changes to the relative magnitude of the 2008 and 2009 shocks. The 2008 effect (φ_8) is now approximately 0, rather than negative, and the 2009 effect (φ_9) is roughly half the size, relative to the column (1) specification. However, the cumulative effects in column (2) is almost identical to column (1) and highly significant, 0.006 (se=0.001). As a basis for comparison, these firms experienced a 5% decline in employment growth between 2008 and 2009.[37]

We also estimated models that control for the exposure of the county to the run-up in housing prices in the 2000's. We use county-level house price data provided to us by Zillow and we control for the interaction of housing price appreciation from 2002-2006 with year dummies. As Appendix Table 4 shows, the estimates are invariant to the inclusion of this control. This is not surprising because Table 3 shows that within state there is only a small and insignificant

[36] Appendix Figures 2 and 3 display the same plots but for total employment.
[37] This figure is based on data from the Census Business Dynamics Statistics.

correlation between housing appreciation and the predicted lending shock. These results suggest that the predicted lending shock measure is not picking up the effects of deleveraging emphasized in Mian and Sufi (2011). These controls are not included in the main model because they are only available for 571 counties thus limiting our sample considerably.

In columns (3)-(4) of Panel A, we report on the estimation the same models for the establishment growth rate for small standalones. [38] The entries in column (4) indicate that a one standard deviation decline in the 2008 and 2009 credit supply shock variable reduces the number of establishments by a statistically significant 0.8% (se =0.2) by the end of 2009.

2. Small Establishments that are Part of Multi-State Firms. Panel B provides an opportunity to contrast these findings with the first set of establishments that should not be directly affected by a local lending shock – small (non-franchise) establishments that are part of firms operating in at least three states. Firms that operate in multiple states should not be greatly affected by the lending conditions in a particular county, at least relative to small standalone firms. The first model in column (1), without controls, shows a similar pattern of estimates as the small standalone category, with a positive relationship between supply and employment growth in 2009 and a negative relationship in 2008. The point estimate for the cumulative effect of the supply shock in 2009 (0.010) is even larger in magnitude than the small standalone category, but is not significant (se=0.009). These estimates confirm our sense that this simple model is inadequate as they may be picking up regional differences in the business cycle.

Once we turn to the richer models with controls, it is evident that the dynamics of chain establishments look much different than for the small standalones. In column (2) of Table 5 Panel B, the 2009 effect (ϕ_9) is now negative and insignificant. The cumulative 2009 effect (π_9) is negative and significant. However, the establishment growth results show little effect of the predicted credit supply shocks by the end of 2009.

Of course, there are reasons why these establishments might be indirectly affected by the lending shock. For example, these firms' products may be substitutes for the standalone firms, in which case the decline in credit for the standalones may allow them to expand their operations. For example, the inability of a standalone operation to replace old equipment or expand its operations may result in more business for establishments that are part of multi-state firms. The estimates are consistent with this possibility. In the richest model in column (2), a one standard deviation decrease in the small business supply shock in 2008 and 2009 increases employment in these firms by about 1.9% by the end of 2009. Thus, this finding suggests that some of the negative effect of the predicted credit supply shocks is counterbalanced by a somewhat less precisely estimated increase in employment among these small establishments that are part of larger firms.

[38] This growth rate is calculated following equation (2).

3. Large Establishments. Panel C repeats this exercise for large establishments--defined as those with at least 100 employees--that are even less likely to rely on local banks for credit due to their size. Using the richer model, the entries fail to suggest a significant statistical relationship between the measures of local predicted credit supply shocks and either employment or the number of establishments. These results are also consistent with the idea that small standalone firms were adversely affected by the local credit shocks and that we are not picking up the some other factor that affected the local economy more broadly.

4. Probing the Robustness of the Results with an Alternative Data Source on Employment by Firm Size. In Table 6, we estimate the same models using the `beta' version of the QWI broken out by firm size. The QWI reports on firms, rather than establishments, so we separately look at small employers (firms less than 20 employees) and large employers (firms 250 employees or more).[39] The QWI does not contain sufficient information to compute growth rates in the preferred way (equation 6), so within a category we simply take the log difference in 4th quarter employment across consecutive years. Because this version of the QWI is missing for a number of states, including California, the sample is smaller than in Table 5. Additionally, the states have staggered entry into the QWI sample, so in order to keep a balanced panel we start the analysis in 2002. For reference, the table includes estimates of the NETS model over the same period and using the same set of counties. One advantage of the QWI is that it allows us to look at payroll or the total wage bill, which is a more complete measure of the reaction of firms than employment, as it incorporates changes in compensation, employment, and hours worked. Our focus in these models will be on the richer within-state specifications with the full set of controls.

The estimates using the QWI sample are largely consistent with those using NETS data. A one standard deviation increase in the lending supply measure in 2008 and 2009 is associated with a 0.6 percentage point increase in employment by the end of 2009 (se=0.3) and a 0.8 (se=0.4) percentage point increase by the end of 2010. The total wage bill results tell a qualitatively similar story. Though somewhat imprecisely estimated, the employment results accord with the NETS data results. To see this more clearly, column (3) shows the estimates using NETS but limiting the sample to the counties that are available in the QWI; the resulting estimates are very close to the QWI results and to the full sample NETS results. As in the NETS sample, we do not observe significant effects of the shocks on employment or total wage bill for large firms (columns 4-5). Overall, the analysis of QWI data provides further evidence that small firms experienced slower growth in response to a reduction in the availability of credit from commercial banks.

[39] The QWI does not have a 100 employee category, so we use a different large employer definition than in the NETS data in Table 5.

5. County-Level Economic Outcomes. Table 7 explores the relationship between the predicted small business credit supply and county-level employment, establishments, and measures of labor earnings. These estimates provide an opportunity to gauge the full county-level effect of credit supply shocks beyond the category of small firms, including any general equilibrium impacts. We consider employment growth from three separate datasets: NETS, CBP, and the QCEW. The CBP and QCEW are essentially designed to measure the same thing, but they are not perfectly correlated, and the literature does not offer guidance on which of these datasets is better for analyses of county employment and earnings dynamics. Thus to reduce measurement error in these analyses, we use the average of the growth rates from the CBP and the QCEW for each county and year. The NETS results are displayed separately so that we can directly compare the magnitudes to those in Table 5 that reported on these outcomes by establishment/firm size. For the CBP/QCEW data the sample runs from 1998-2010 while for the NETS it continues to run for 1998-2009. The table only shows estimates from the preferred richer model with controls, including state by year fixed effects.

The estimates for total employment and establishment present a mixed picture. As expected, the magnitudes for the effect of small business credit shocks on total county employment are smaller than for the small firm sample. The cumulative effect of -1 standard deviation shocks in 2008 and 2009 on 2009 employment is -0.2% for the CBP/QCEW sample and -0. 3% for the all private sector NETS sample, compared to -0.6% in the small firm NETS sample. [40] Even though the estimates for the CBP/QCEW and all private sector NETS sample are close to each other, only the NETS estimate is (borderline) significant with a standard error of 0.17%. With respect to the establishment results, the NETS data indicate that the predicted credit supply shocks have a strong positive relationship with establishment growth while the CBP/QCEW data lead to a less definitive conclusion.

In contrast, there is relatively strong evidence on the effect of predicted credit supply shocks on the total wage bill (column (5)) and average earnings per worker (column (6)). The total wage bill results from the CBP/QCEW sample in column (5) indicate that 2010 payroll was -0.66% (standard error=0. 33%) lower in counties with -1 standard deviation predicted credit supply shocks in 2008 and 2009. This effect seems to be largely driven by reductions in average earnings as column (6) reports that these credit shocks are associated with a 0.70% (standard error = 0.27%) decline in earnings per worker. Since the number of hours worked is unobserved, it is unclear if these results reflect fewer hours worked or a decline in real wages for the employed.

To summarize, there are some differences in magnitudes across datasets, and estimates are not uniformly significant. Broadly, however, the evidence points to there being a modest positive

[40] It is not possible to obtain reliable estimates of population changes over these years, so it is unclear whether there shocks affected outmigration or employment to population ratios.

association between the small business credit supply shock variables and county-level employment and earnings during the Great Recession.

C. The Role of Small Business Loans in "Normal" Economic Settings

Up to now we have considered the effects of the credit shocks that occurred over the 2007-2009 period. However, the methodology we use to construct the predicted lending shock can be used to assess how shocks affected the real economy during less volatile times. To this end, we extend the analysis to include shocks dating back to 1999 and employ a model that incorporates all of the shocks simultaneously.

We first estimate the following model:

$$(8) \qquad \ln(l_{it}) = w_{1t}p_t + w_{2t}p_{t-1} + w_{3t}p_{t+1} + \delta_{st} + \beta X_{it} + v_t + \gamma_i + \varepsilon_{it},$$

where l_{it} are loan originations in county *i* and year *t*. The covariates include state by year fixed effects, δ_{st}, the standard county characteristics controls measured in 2006 (X_{it}) whose effect is allowed to vary by year, and county fixed effects, γ_i.

The primary variables of interest are the predicted credit supply shocks in year t, p_t, that are calculated as outlined in equation (4). The model allows the effect of a shock to persist over two periods. Further, we allow these effects to differ by calendar year. Finally, we also include a lead term in the shock as a specification check as a shock in *t+1* should not affect lending in *t*.

Figure 10 plots the effect of the shock originating in each year. Specifically, for every year *t* we plot the sum of ω_{1t} and ω_{2t+1}, which is the effect of a +1 standard deviation credit supply shock that occurred in period *t* on lending in *t* and *t+1*. The dotted lines represent 95 percent confidence interval, allowing for a sense of the precision.

It is apparent that the relationship between predicted lending and actual lending is highly significant in all years, but displays a counter-cyclical pattern with a point estimate that is almost 5 times larger in 2009 than 2004. We believe that this asymmetry is an inherent feature of the shift-share approach, because it is easier to predict where lending will decline than where lending will grow.[41]

Figure 11 is analogous to Figure 10 except for the outcome variable, which is small standalone employment growth. The figure visually shows that the effects we estimated in 2008 are not

[41] The estimated coefficient (standard error) for the average of the lead terms of the predicted credit supply shock, ω_{1t}, is -0.0002 (0.0003), indicating that future credit supply shocks do not significantly affect loan originations. The lack of significance of the lead terms supports the validity of our specification.

evident in earlier years.[42] Prior to 2008 the estimated response is statistically insignificant and the point estimates are mostly in the negative direction.

To estimate the differences in magnitudes more precisely and to assess statistical significance, we estimate a model that constrains the effect of the predicted lending shock to be the same for all years, but allowing for a shift in 2008 and 2009. For loan originations, the estimating equation is:

$$\ln(l_{it}) = \theta_1 p_{it} + \theta_2 p_{it-1} + \theta_3 1(t = 2008) p_{it} + \theta_4 1(t = 2009) p_{it-1} \quad (9)$$
$$+\theta_5 1(t = 2009) p_{it} + \theta_6 1(t = 2010) p_{it-1} + \beta X_{it} + \gamma_i + \delta_{st} + \varepsilon_{it}.$$

In addition to reporting the estimated θ parameters we report the total effect of the 2008 shock ($\theta_1 + \theta_2 + \theta_3 + \theta_4$), the total effect of the 2009 shock ($\theta_1 + \theta_2 + \theta_5 + \theta_6$), and the excess effect of the 2008 and 2009 shocks, which are ($\theta_3 + \theta_4$) and ($\theta_5 + \theta_6$), respectively. We estimate the same model for total county employment payroll growth rates. For the small firm NETS sample, we cannot include the $\theta_6 1(t = 2010) p_{it-1}$ term because we lack 2010 data.

Table 8 presents these estimates. Consistent with Figure 10, there is a strong relationship in all years of the sample, but a much larger effect in the 2008-2009 period. With respect to employment, the shock terms for the pre-2008 period are small and statistically insignificant for small standalone firms. The impact of the 2008 shock is roughly the same magnitude as estimated in Table 5, and the difference in effects between 2008 and 2009 and the early years is significant.

The evidence for county-level outcomes generally suggest that negative predicted credit supply shocks during the Great Recession are associated with declines in economic activity but some of the estimates are imprecise. For full county employment, we find insignificant effects for the pre-2008 shocks, and significant effects for the 2008 shocks in NETS sample and the 2009 shock in the CBP/QCEW sample. We can reject equality of these effects between pre-2008 and 2008/2009 for the NETS sample, though this difference is not statistically significant in the CBP/QCEW sample. In the case of the total wage bill in column (5), the total effect of the 2008 predicted credit supply shock is statistically different than in the earlier years, while the 2009 shock is of a similar magnitude but would not be judged to be statistically significant by conventional criteria.

We conclude that there was something different about the response of firms to the predicted credit supply-shocks in the 2008-2010 period, relative to the 1999-2007 period. In fact, we find that in the earlier years, bank lending supply-shocks have an insignificant impact on measures

[42] The effect of the 2009 shock is not shown because we lack 2010 data, though as seen Table 8 this shock does not have a significant effect on small business employment growth in 2009. It remains to be seen whether the effect grows over time.

of economic activity. With respect to measured bank lending, this might be the case because the entire banking sector was in particularly dire financial health in this period, such that even relatively healthy banks may have judged it too risky to start new lending relationships in this period. Of course, economic activity is responsive to changes in total credit availability, not just credit from banks. It seems plausible to presume that most of their alternative sources of credit for small businesses were also restricted during the 2007-9 period with home equity loans serving as a prime example of a source of credit for small businesses that was also constrained during this period.

VI. Interpretation

Applying the cross-sectional effects of these supply shocks to aggregate time-series variation in aggregate small business lending is not straightforward. One must determine how much of the overall change in small business lending nationally was due to supply-shifts rather than demand shifts, and incorporating general equilibrium effects of the shocks are non-trivial.

We instead conduct a simple bounding exercise where the goal is to assess the magnitudes of the estimates. Specifically, we obtain an upper-bound estimate of the aggregate effects by assuming that the entire reduction in small business lending between 2007 and 2009 was driven by the credit supply decisions of banks. Clearly this will result in an overestimate of the overall effect of reduced lending, because at least some of the reduction in lending is due to lower demand for credit as a result of the recession and a more elevated risk of business default.

The first step in this exercise is to note that CRA disclosed small business lending declined by 22% in 2008 and 33% in 2009. Assuming that these represent supply shifts, we can apply these shifts to our estimates to assess the magnitude of the aggregate impact of the 2007-2009 lending shocks on small business employment growth and county-level economic activity.

The second step is the estimation of a two stage least squares (2SLS) model where the employment, establishment, earnings, and payroll variables are the dependent variables. The regressors of interest are contemporaneous and lagged log loan originations. The instruments for these regressors are the interaction of the 2008 lending shock with 2008 and 2009 dummies, and the 2009 shock with the 2009 year dummy. Additionally, the model includes all main effects, state by year fixed-effects, and the standard set of county characteristic controls interacted with year dummies. Thus, the first-stages are laid out in versions of equation (7) where the dependent variables are contemporaneous and lagged log loan originations. These

models are estimated on data from 1998 through 2009 to ensure comparability across the three data sets.[43]

The 2SLS estimates are reported in Table 9. All entries can be interpreted as elasticities as the outcomes are the natural log difference and the endogenous variables are the natural log of the loan origination rate. Column (1) reports the estimates for the small standalone category from the NETS data. Employment growth depends on both loan originations in the current period and the lagged period. In the current period the elasticity of employment growth with respect to loan originations is 0.017 with an elasticity on the lag of 0.021. We also report the standard 2SLS diagnostics for an overidentified model: The first stage Angrist-Pischke F-statistic is large for both first stage equations and the Hansen J statistic for overidentification fails to reject the null hypothesis that the instruments are exogenous.

The 2SLS estimates imply that the national changes in small business lending (22% in 2008 and 33% in 2009) resulted in a reduction of small business employment growth of 0.37 percentage points (=0.22*0.017) in 2008 and 1 percentage point in 2009 (=0.33*0.017+0.22*0.021). Together, these results suggest that an upper bound estimate is that small business employment was 1.4 percentage points lower at the end of 2009 due to the reduction in small business lending. Thus, this upper bound estimate accounts for up to 20% of the 7 percent decline in small business employment between 2007 and 2009 for firms with less than 20 employees. The column (2) results suggest that the decline in small business lending also reduced the number of small establishments in 2008 and 2009.

Columns (3) through (5) report on the aggregate economy, rather than just focusing on small establishments. A similar calculation on the effect of total employment shows modest upper bound effects of 0.1 percentage points in 2008 and 0.6 in 2009 (column 3).[44] Thus, these results suggest that an upper bound estimate is that the reduction in small business lending accounted for a decline in total employment of 0.7 percentage points by the end of 2009, which is about 16 percent of the 5 percentage point decline in total employment between 2007 and 2009. The QCEW/CBP dataset shows a larger upper bound estimate of 0.7 and 0.5 percentage point effect on the wage bill for 2008 and 2009 respectively (column 5). According to this exercise, the decline in small business lending accounted for a 1.2 percentage point decline in the total wage bill or approximately 30% of the total decline in real aggregate wages between 2007 and 2009.

[43] Appendix Table 5 reports on the corresponding OLS models.

[44] Column (3) uses the average of the QCEW, CBP, and NETS but we note that the estimate is somewhat sensitive to the data source. For example, the average of the QCEW and CBP data files indicates an upper bound effect by the end of 2009 of -0.2 percentage points, while the results from the NETS data file suggest an upper bound effect of -1.1 percentage points.

VII. Conclusion

This paper has used a new identification strategy and what we believe is the most comprehensive data set ever assembled to investigate the role of bank lending on the real economy. Specifically, we develop a new measure of local credit supply shocks for small businesses that is based on the market shares of the banks that served a county before the crisis and the national change in each bank's lending that is attributable to supply factors (e.g., due to differences in the crisis' effect on their balance sheets). The analysis finds that the 2008 and 2009 measures of local credit supply shocks are associated with sharp declines in total county-level small business loan originations. For example, we find that a one standard deviation reduction in the 2008 and 2009 measures of local credit supply shocks is associated with a 17% reduction in total county-level small business loan originations in 2009, indicating that, at least in the near term, businesses are unable to switch lenders.

The paper then assesses the effect of the credit supply shocks on the real economy. A one standard deviation reduction in the 2008 and 2009 measures of local credit supply shocks depress 2009 levels of small establishment employment by 0.6 percentage points, small establishments by 0.8 percentage points, and county-level payroll and earnings by 0.65 percentage points. Upper bound estimates suggest that the 2007-9 decline in small business lending accounted for up to 20% of the 7 percentage point decline in small business employment, 16% of the 5 percentage point decline in total employment, and 30% of the 4 percentage point decline in real aggregate wages during this period. Finally, we note that the relationship between lending supply and economic activity is not evident in the 1997-2007 period, underscoring the unique circumstances during the Great Recession.

These results are also informative, although unlikely to be dispositive, about a series of policy issues. The banking industry is heavily regulated and, as the extraordinary response to the recent financial crisis demonstrates, governments are willing to extend significant aid to banks in moments of financial stress. In the United States, these policies included capital injections through the Toxic Assets Relief Program, nearly costless loans from the Federal Reserve to banks, and stress tests. It is striking that this paper's results are evident, even in the presence of these policies, and it seems likely that there would have been even larger credit shocks and resulting impacts on the broader economy in their absence.

We close with two further observations. First, it may be appropriate to take the limited impact of credit shocks on the real economy during the "normal" period of 1997-2007 as evidence that proposals for new programs that aim to increase banks' supply of credit are unnecessary. It appears that in normal times, borrowers are able to access other sources of credit or in some other way make do without impacting the real economy. Second, this paper does not provide any evidence on the moral hazard consequences of policies to support banks and thus full welfare calculations of such policies are not feasible.

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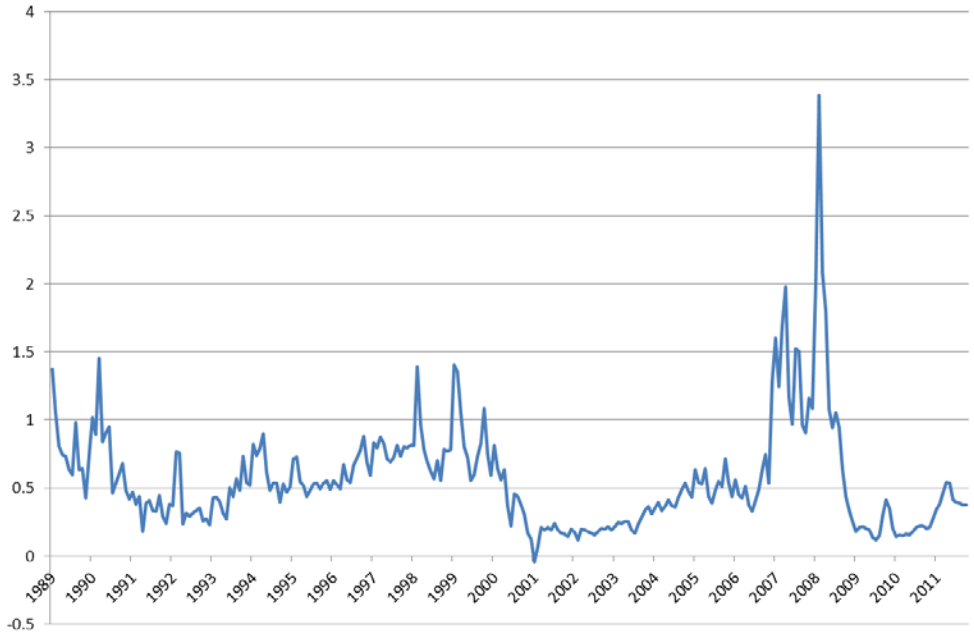
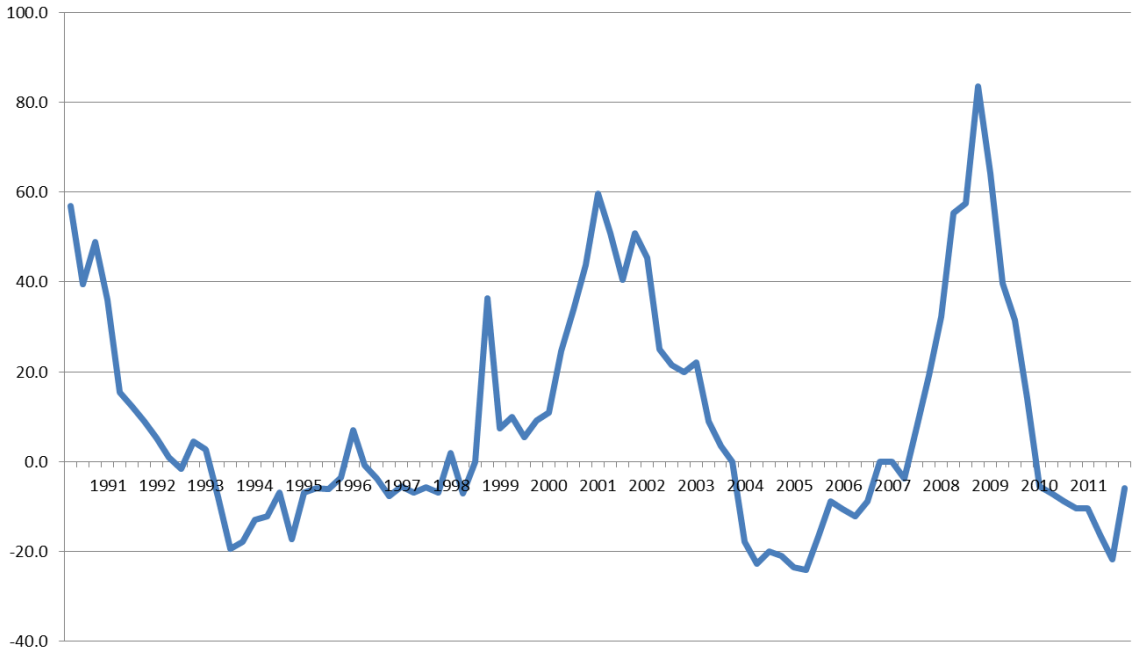
Figure 1
TED Spread, 1989 - 2012



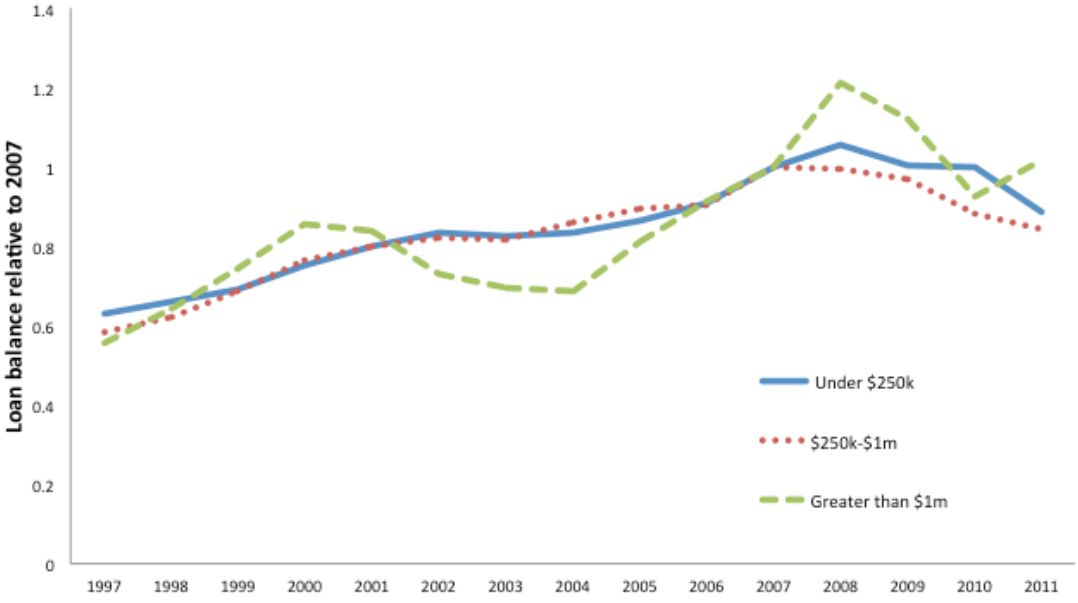
Source: Federal Reserve Board of Governors and http://www.fedprimerate.com

Figure 2: Net Percentage of Domestic Respondents Tightening Standards for Commercial and Industrial Loans Large and Medium Firms



Source: Federal Reserve Board of Governors

Figure 3: Loan balances by loan size relative to 2007



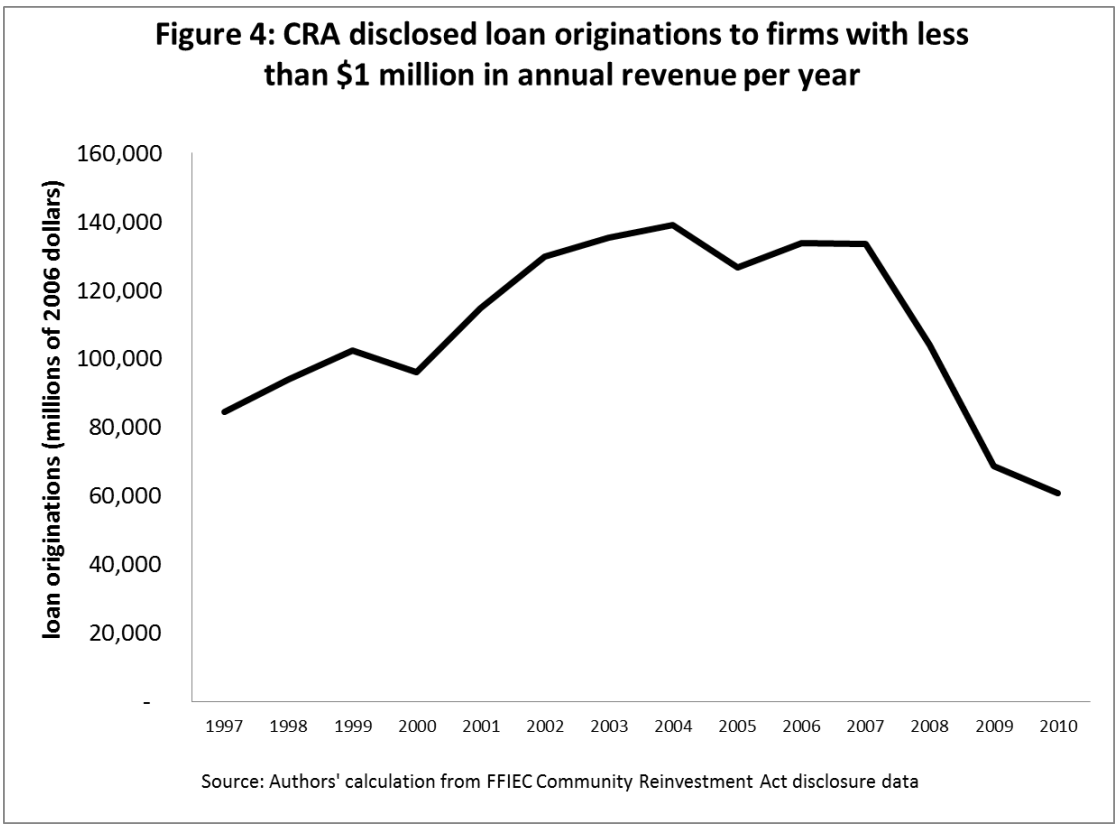


Figure 5: Kernel Density Plot

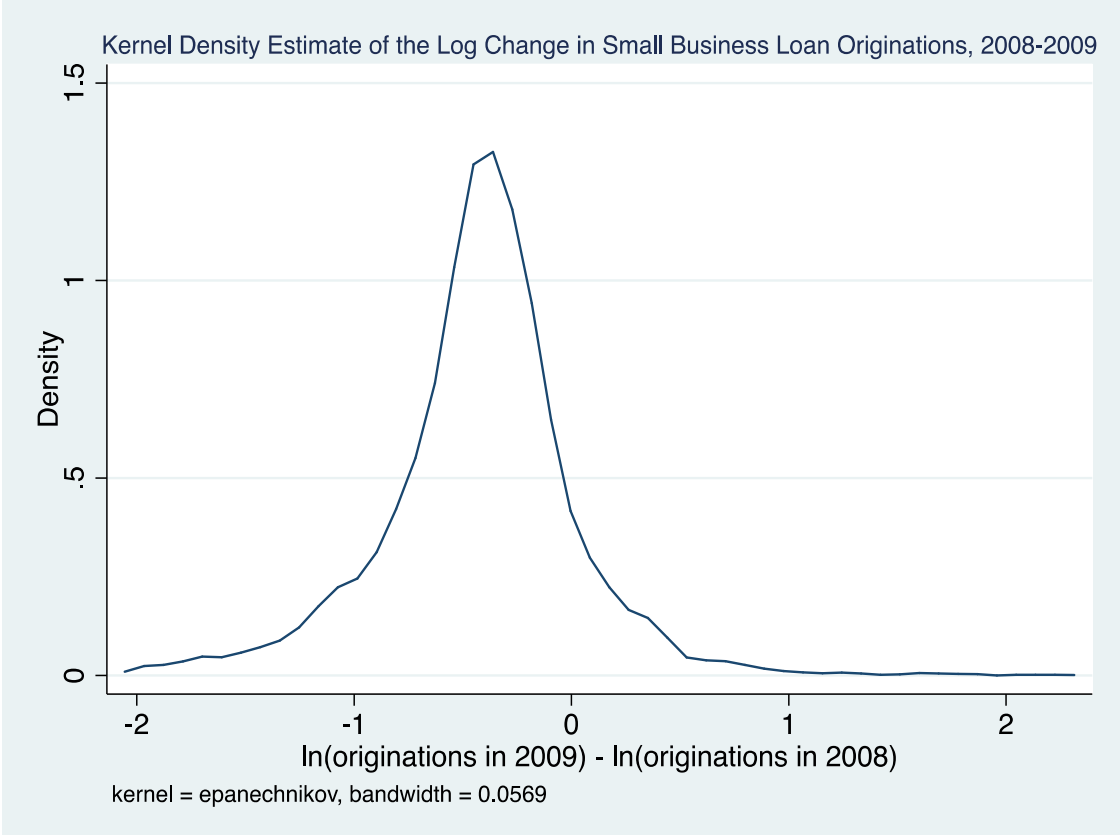


Figure 6: Adjusted Predicted Credit Shock by County

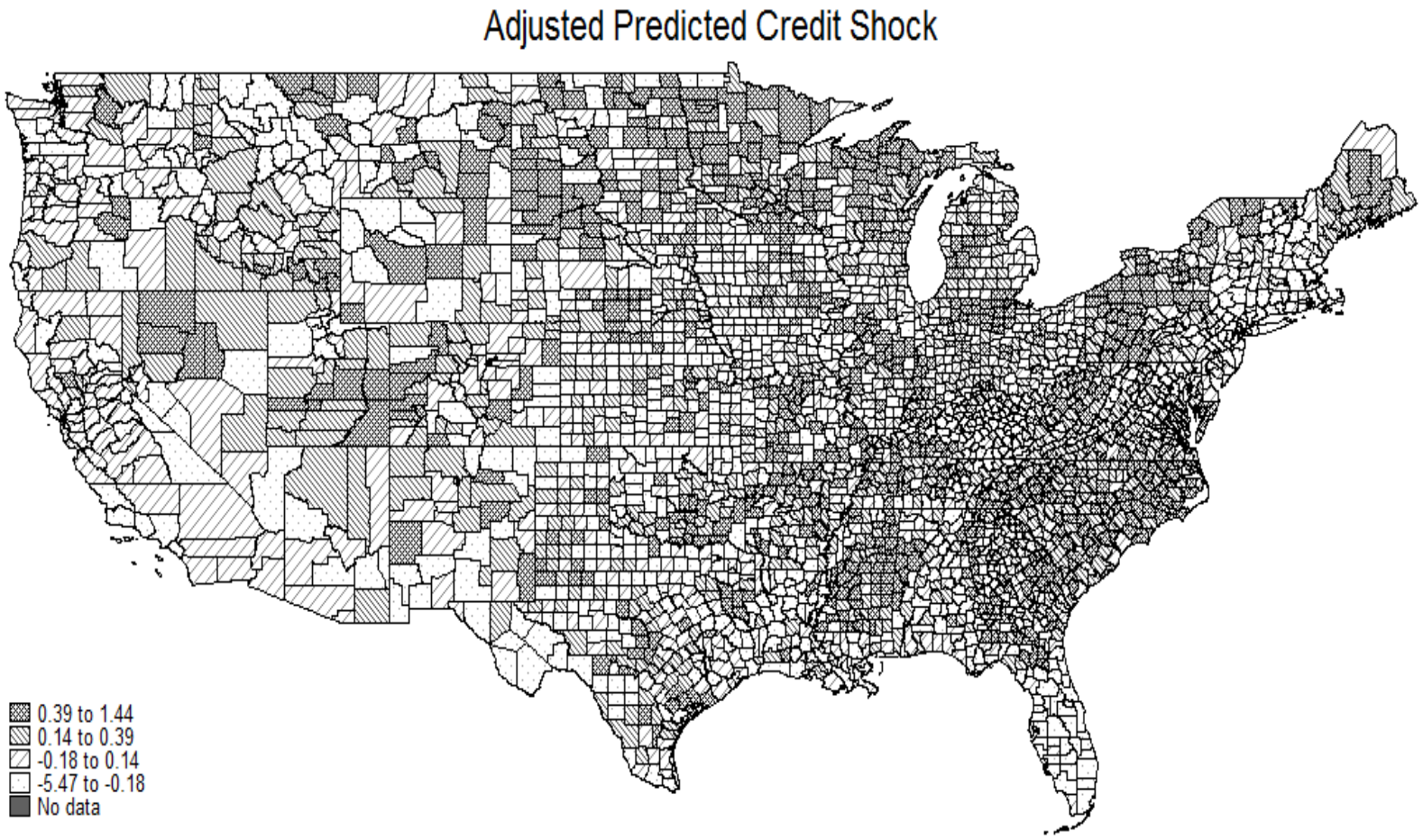


Figure 7: Adjusted Predicted Credit Shock by County, TX

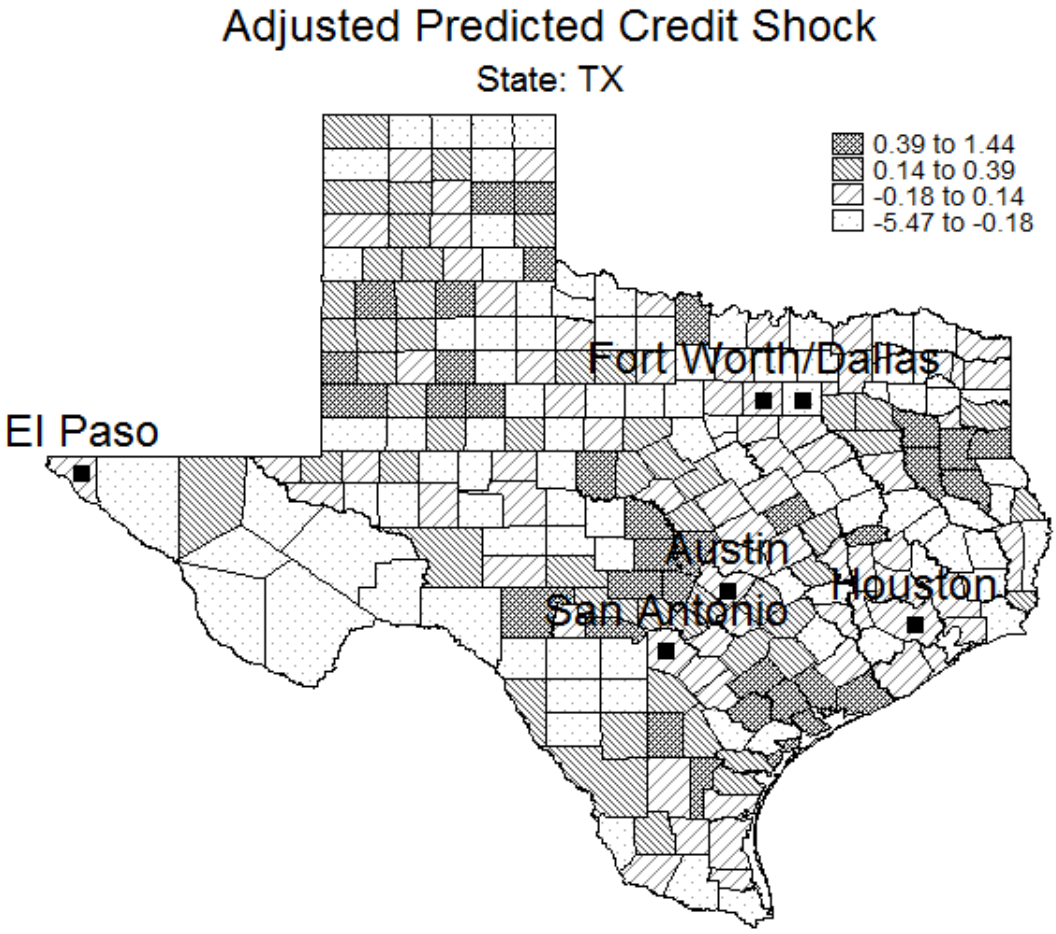
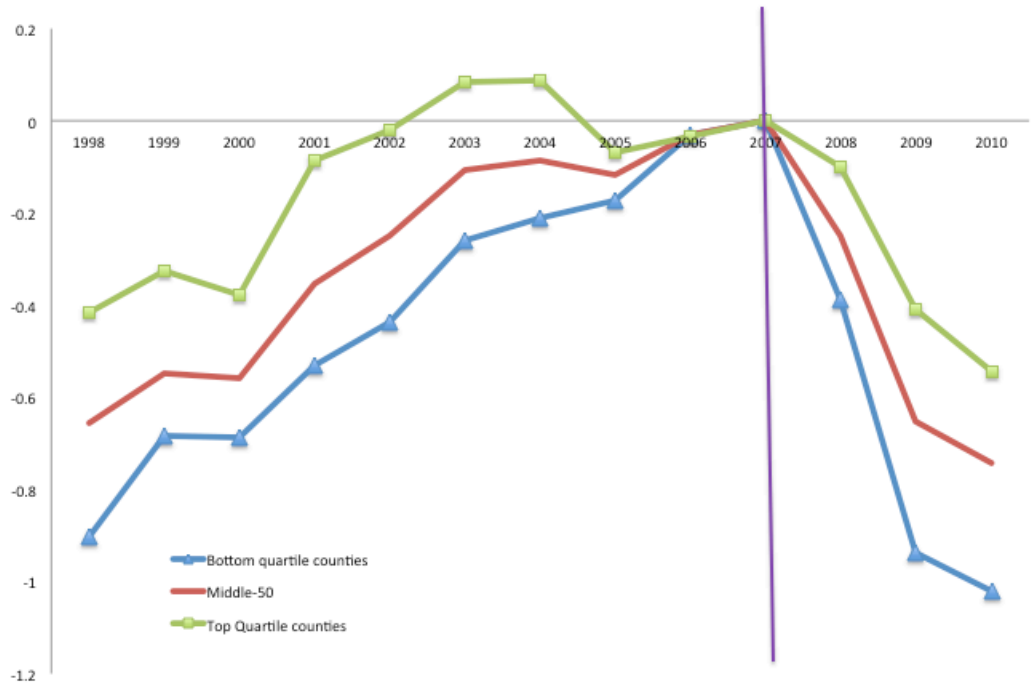
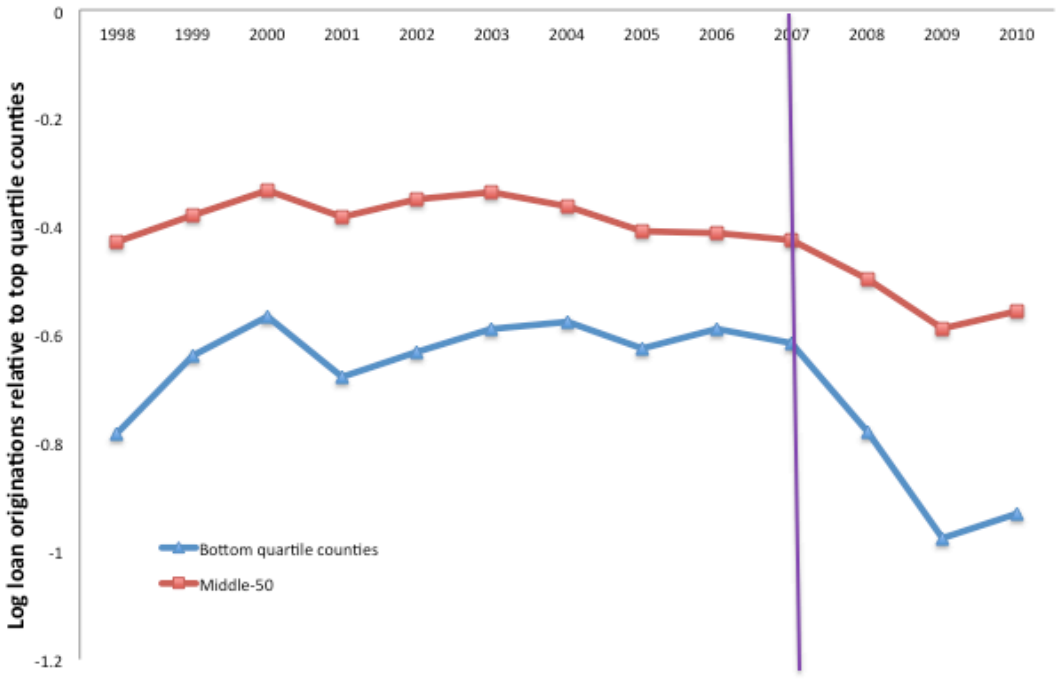


Figure 8a: ln(small business loan originations) relative to 2007



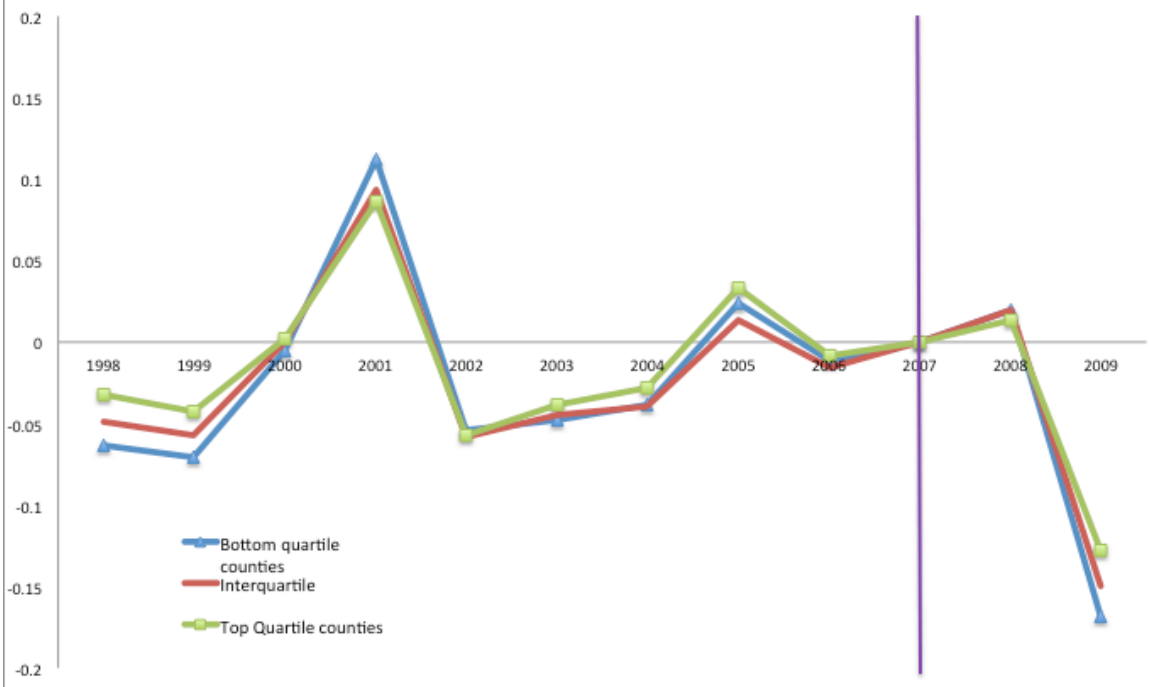
Notes: Figure is based on estimation of equation (5). Quartiles refer to the predicted lending shock measure defined in equation (4) See text for further details.

Figure 8b: Regression-adjusted difference in log lending between top quartile counties and lower quartile counties



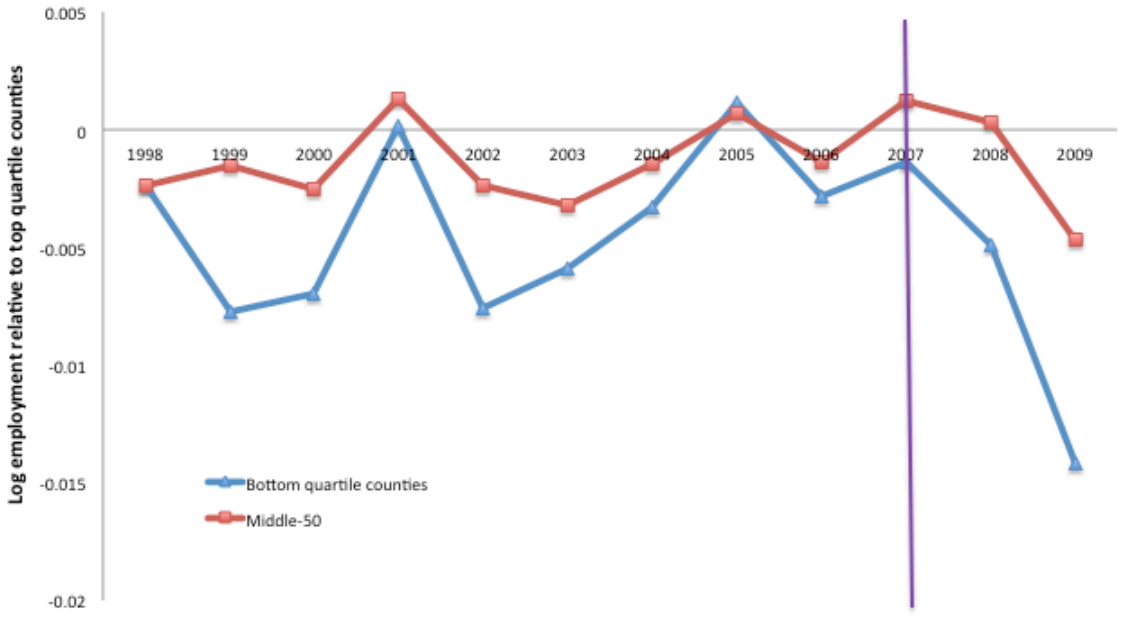
Notes: Figure is based on estimation of equation (6). Quartiles refer to the predicted lending shock measure defined in equation (4) See text for further details.

Figure 9a: Employment growth rate in small (<20) standalone business employment relative to 2007



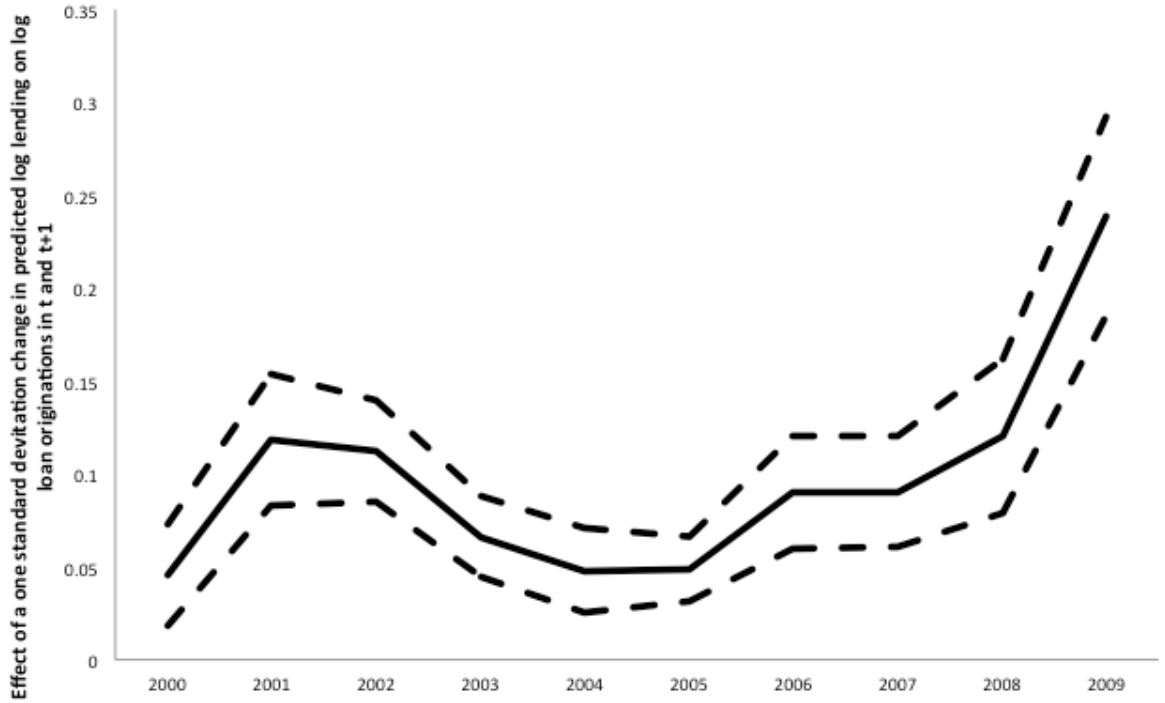
Notes: Figure is based on estimation of equation (5) where the dependent variable is the employment growth rate for small standalone firms, defined as single unit establishments with fewer than 20 employees. Quartiles refer to the predicted lending shock measure defined in equation (4). See text for further details.

Figure 9b: Regression-adjusted difference in employment growth rates of small standalone businesses between top quartile counties and lower quartile counties



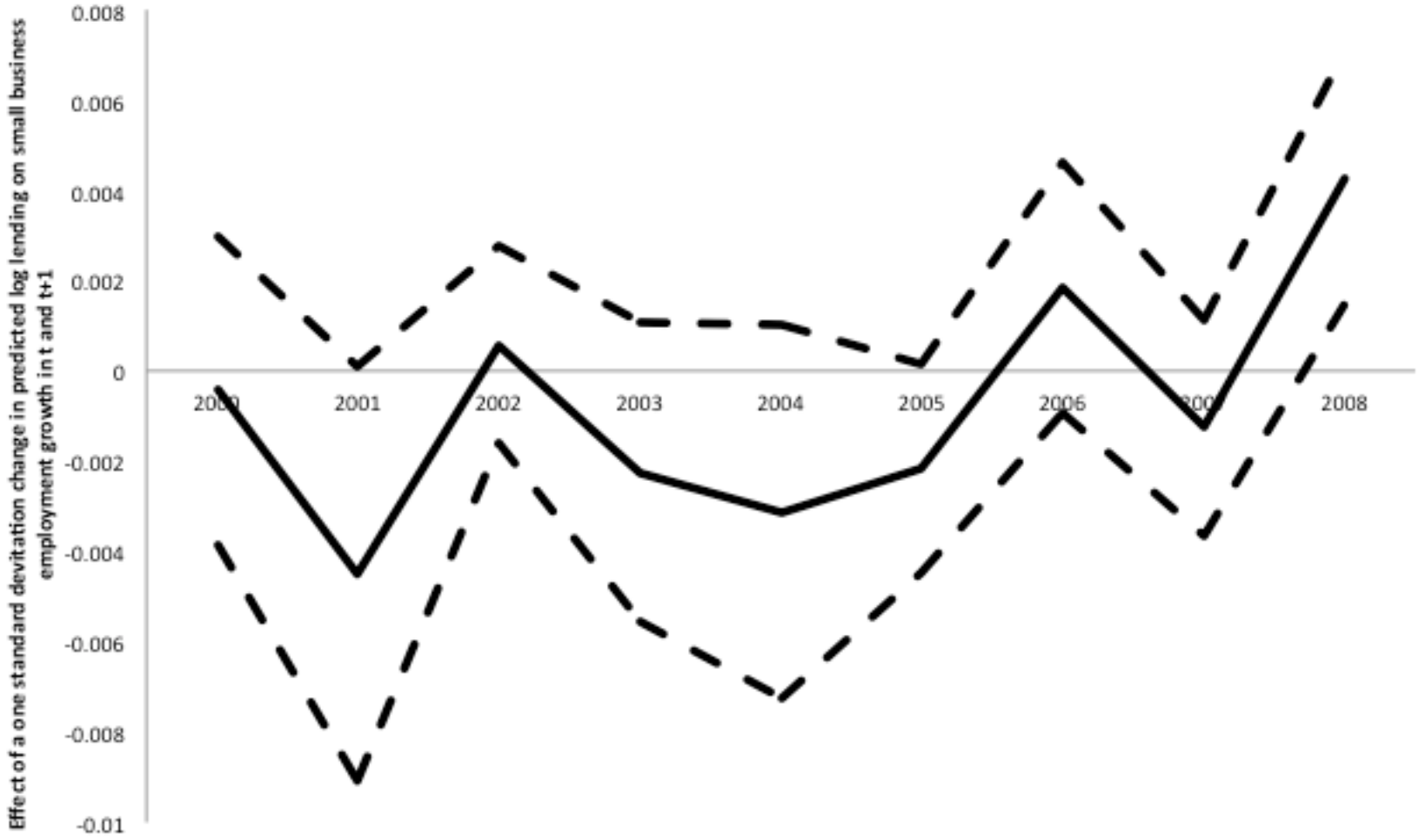
Notes: Figure is based on estimation of equation (6) where the dependent variable is the employment growth rate for small standalone firms, defined as single unit establishments with fewer than 20 employees. Quartiles refer to the predicted lending shock measure defined in equation (4) See text for further details.

Figure 10: Effect of predicted lending shock on loan originations by year



Notes: Figure is based on estimation of equation (8) where the dependent variable is ln small business loan originations. See text for further details.

Figure 11: Effect of predicted lending shock on small business employment growth by year



Notes: Figure is based on estimation of equation (8) where the dependent variable is the employment growth rate for small standalone firms, defined as single unit establishments with fewer than 20 employees. See text for further details.

Table 1: Changes in lending between 2007-2009 for selected large bank holding companies

	Percent change in small business CRA-reported lending, 2007-2009	Percentile: Log change in small business CRA-reported lending market share 2007-2009 (low is worse)	Percentile: Log change in CRA-reported lending 2007-20089 adjusted for county market shares in 2007 (low is worse)
	(1)	(2)	(3)
Bank of New York Mellon	-89.9	2	3
JP Morgan Chase	-88.5	2	2
Citigroup	-83.6	4	6
Bank of America	-77.2	6	9
Wachovia	-57.0	18	22
Capital One Financial	-79.5	5	5
Suntrust Banks	-41.8	34	36
Regions Financial	-37.7	38	34
Wells Fargo	-33.1	44	59
HSBC	-31.9	45	71
BB&T	-19.5	60	58
PNC Financial	-33.2	43	44
US Bancorp	-3.3	76	78
Median across all CRA reporting banks	-32		
All banks combined	-48		

Note: Column 1 is the percent change in small loan originations to firms with less than $1m in gross revenue between 2007-2009, as reported to FFIEC. Column 2 is the percentile of the change in CRA lending across all holding companies that meet the criteria for CRA disclosure. Column 3 is the percentile in the change in CRA lending after partialling out county fixed-effects.

Table 2: County characteristics

	Above median in predicted lending shock	Below median in predicted lending shock	p-value on t-test for difference	Above median - Below median in predicted change in lending (within state)	p-value on t-test for within-state difference
	(1)	(2)	(3)	(4)	(5)
Employment growth 2002-2006 [n=3117]	0.042 [0.114]	0.042 [0.132]	0.97	0.005 [0.005]	0.351
Wage growth 2002-2006 [n=3117]	0.142 [0.078]	0.154 [0.087]	0.00	0.000 [0.003]	0.965
Home price appreciation 2002-2006 [n=571]	0.327 [0.020]	0.449 [0.203]	0.00	-0.014 [0.014]	0.321
% Change in Total Bank Lending 2002-2006 [n=3138]	0.022 [0.609]	0.108 [0.772]	0.001	-0.039 [0.028]	0.168
Log median per capita income 2006 [n=3140]	10.585 [0.220]	10.580 [0.270]	0.62	0.012 [0.009]	0.172
Poverty rate 2006 [n=3141]	15.363 [5.950]	15.507 [6.728]	0.56	-0.064 [0.217]	0.767
Construction share in 2006 [n=3115]	0.066 [0.043]	0.064 [0.051]	0.484	0.002 [0.002]	0.335
Manufacturing share in 2006 [n=3073]	0.180 [0.129]	0.149 [0.136]	0.00	0.006 [0.005]	0.208
ln(density in 2006) [n=3113]	-10.860 [1.567]	-11.190 [1.929]	0.00	0.309 [0.055]	0.000
ln(poulation in 2006) [n=3114]	10.347 [1.303]	10.098 [1.670]	0.00	0.340 [0.052]	0.000

Notes: Standard deviations in brackets. Employment growth, wage growth, construction share, and manufacturing share are from the QCEW. Change in lending is from the FFIEC. Per capita income, poverty rates, population and density data are from the Census. Home values are from Zillow. Column 4 is obtained from a regression of the county characteristic on an indicator for above median with state fixed-effects.

Table 3: Testing for spatial sorting in bank lending shocks

	County-level data	Bank-level data
	(1)	(2)
	Dependent variable: Fixed-effect of the bank with the largest market share in the county	Dependent variable: Bank fixed-effect
Constant	0.517 (0.042)	0.618 (0.031)
Fixed-effect of the bank with the second largest market share in the county	-0.067 (0.058)	
Average competitor bank fixed-effect in counties were the bank operates		0.078 (0.096)
Observations	2388	654
R-squared	0.0061	0.001

Notes: Robust standard errors in parentheses. Model 1 is an OLS regression of the fixed-effect of the bank with the largest market share in the county on the fixed-effect of the bank with the second highest market share, weighted by the number of establishments in the county in 2006. The bank fixed-effects are estimated from a regression of the log change in small business lending by county and bank between 2007 and 2009 on county and bank holding company fixed effects weighted by 2007 lending. Model 2 is a regression of each bank holding company's fixed-effect on the average bank fixed-effect in counties where the bank operates. To compute the average bank fixed-effect, we calculate the dollar weighted average bank fixed-effect in every county excluding bank i, and then we aggregate up these averages to the bank holding company level weighting by the share of bank i's lending in the county.

Table 4: Relationship between predicted lending shock and ln(loan originations)

	(1)	(2)
2008 shock * 2008	0.003	0.073
	(0.010)	(0.008)
2008 shock * 2009	0.023	0.084
	(0.012)	(0.013)
2008 shock * 2010	0.024	0.088
	(0.011)	(0.011)
2009 shock * 2009	0.122	0.114
	(0.011)	(0.010)
2009 shock * 2010	0.108	0.095
	(0.011)	(0.010)
φ_8: Effect of shocks in 2008	0.003	0.073
	(0.010)	(0.008)
φ_9: Effect of Shocks in 2009	0.136	0.169
	(0.013)	(0.011)
φ_{10}: Effect of Shocks in 2010	0.129	0.176
	(0.012)	(0.010)
π_9: Cumulative effect of shocks through 2009	0.138	0.242
	(0.020)	(0.017)
π_{10}: Cumulative effect of shocks through 2010	0.267	0.417
	(0.030)	(0.025)
F-test of joint significance of shock interactions (p-value)	0.000	0.000
Observations	40404	39273
County characteristics * year dummy		X
State * year effects		X

Notes: The entries are based on the estimation of equation (7). Standard errors clustered on county in parentheses. An observation is a county by year cell. Shocks refer to predicted loan originations as specified in equation (4). The sample spans 1998-2010. County characteristics are 2006 values of log population density, log population, construction share, manufacturing share, and log per capita income. All main effects are included. See the text for further details.

Table 5: Effect of Predicted Lending Shock on Employment and Establishment Growth Rates by Size of Firm; NETS database

Panel A	Small (less than 20 employee) standalone firms			
	Employment growth rate		Establishment growth rate	
	(1)	(2)	(3)	(4)
2008 shock * 2008	-0.004	0.001	-0.005	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
2008 shock * 2009	0.014	0.004	0.019	0.004
	(0.003)	(0.001)	(0.004)	(0.001)
2009 shock * 2009	-0.004	0.001	-0.005	0.002
	(0.002)	(0.001)	(0.003)	(0.001)
φ_8: Effect of shocks in 2008	-0.004	0.001	-0.005	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
φ_9: Effect of Shocks in 2009	0.010	0.005	0.014	0.006
	(0.002)	(0.001)	(0.003)	(0.001)
π_9: Cumulative effect of shocks through 2009	0.006	0.006	0.009	0.008
	(0.003)	(0.001)	(0.004)	(0.002)
F-test of joint significance of shock interactions (p-value)	0.00	0.00	0.00	0.00
Observations	37332	36252	37332	36252
County characteristics*year dummies		X		X
State * year effects		X		X

Table 5 (Continued)

Panel B	Small establishments that are part of multi-state firms			
	Employment growth rate		Establishment growth rate	
	(1)	(2)	(3)	(4)
2008 shock * 2008	-0.006	-0.014	-0.005	-0.003
	(0.005)	(0.007)	(0.001)	(0.001)
2008 shock * 2009	0.013	-0.003	0.008	0.003
	(0.004)	(0.004)	(0.002)	(0.002)
2009 shock * 2009	0.003	-0.003	0.003	-0.001
	(0.005)	(0.004)	(0.003)	(0.002)
φ_8: Effect of shocks in 2008	-0.006	-0.014	-0.005	-0.003
	(0.005)	(0.007)	(0.001)	(0.001)
φ_9: Effect of Shocks in 2009	0.015	-0.005	0.011	0.002
	(0.006)	(0.004)	(0.003)	(0.002)
π_9: Cumulative effect of shocks through 2009	0.010	-0.019	0.006	-0.001
	(0.009)	(0.008)	(0.004)	(0.002)
F-test of joint significance of shock interactions (p-value)	0.00	0.176	0.00	0.00
Observations	37167	36139	37167	36139

Table 5 (Continued)

Panel C	**Large Establishments (at least 100 employees)**			
	Employment growth rate		Establishment growth rate	
	(1)	(2)	(3)	(4)
2008 shock * 2008	0.003	0.000	0.000	0.001
	(0.002)	(0.004)	(0.001)	(0.001)
2008 shock * 2009	0.005	0.003	0.003	0.002
	(0.002)	(0.003)	(0.001)	(0.001)
2009 shock * 2009	-0.004	-0.004	-0.002	-0.002
	(0.002)	(0.003)	(0.001)	(0.001)
φ_8: Effect of shocks in 2008	0.003	0.000	0.000	0.001
	(0.002)	(0.004)	(0.001)	(0.001)
φ_9: Effect of Shocks in 2009	0.001	-0.001	0.001	0.001
	(0.002)	(0.003)	(0.001)	(0.002)
π_9: Cumulative effect of shocks through 2009	0.004	-0.001	0.001	0.001
	(0.003)	(0.004)	(0.002)	(0.002)
F-test of joint significance of shock interactions (p-value)	0.01	0.39	0.02	0.33
Observations	35020	34423	35020	34423

Notes: The entries come from the fitting of versions of equation (7) on data from the NETS database. Standard errors clustered on county are in parentheses. An observation is a county by year cell. The sample spans 1998-2009. Shocks refer to predicted loan originations as specified in equation (4). Small establishments are defined as less than 20 employees. Large establishments are defined as at least 100 employees. Multi-state firms are defined as firms that operate in at least three states. County characteristics are 2006 values of log population density, log population, construction share, manufacturing share, and log per capita income. All main effects are included. All models are weighted by the number of establishments in the county in 2006. See the text for further details.

Table 6: Effect of Predicted Lending Shock on Employment, Establishment and Payroll Growth Rates by Size of Firm; Quarterly Workforce Indicators

	Small Firms (QWI)		Small Standalone Firms (NETS)	Large Firms (QWI)	
	Employment growth rate	Wage Bill growth Rate	Employment growth rate	Employment growth rate	Wage Bill growth Rate
	(1)	(2)	(3)	(4)	(5)
2009 shock * 2010	0.001	-0.003		-0.005	-0.001
	(0.003)	(0.003)		(0.004)	(0.004)
2009 shock * 2009	-0.003	-0.003	0.002	-0.006	-0.008
	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)
2008 shock * 2010	0.001	0.003		-0.003	0.000
	(0.002)	(0.003)		(0.003)	(0.003)
2008 shock * 2009	0.006	0.009	0.004	0.000	0.006
	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)
2008 shock * 2008	0.003	0.002	0.001	0.002	0.000
	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)
φ_8: Effect of shocks in 2008	0.003	0.002	0.001	0.002	0.000
	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)
φ_9: Effect of shocks in 2009	0.003	0.006	0.005	-0.006	-0.002
	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)
φ_{10}: Effect of shocks in 2010	0.002	0.000		-0.008	-0.002
	(0.003)	(0.004)		(0.003)	(0.004)
π_9: Cumulative effect of shocks through 2009	0.006	0.008	0.007	-0.004	-0.002
	(0.003)	(0.004)	(0.002)	(0.004)	(0.005)
π_{10}: Cumulative effect of shocks through 2010	0.008	0.008		-0.011	-0.004
	(0.004)	(0.005)		(0.006)	(0.006)
F-stat on shocks	0.03	0.02	0.00	0.05	0.38
Observations	23050	22972	20387	12026	11214

Notes: The entries come from the fitting of versions of equation (7) to data from the Quarterly Workforce Indicators database. Standard errors clustered on county in parentheses. An observation is a county by year cell. The sample spans 1998-2010. All models include state by year fixed effects and the interaction of county characteristics with year dummies. County characteristics are 2006 values of log population, log density, construction share, manufacturing share, and log per capita income. Shocks refer to predicted loan originations as specified in equation (4). Small establishments are defined as less than 20 employees. Large establishments are defined as at least 250 employees. Data from NETS in Column 3 reflects the same counties as the QWI sample. All main effects are included. Employment growth rate is defined as the change in within category county employment over consecutive years. Establishment and payroll growth rates are computed the same way. Column 3 uses the same model and data from Table 5 but only with the counties that are included in the QWI sample. All models are weighted by the number of establishments in the county in 2006. See the text for further details.

Table 7: Effect of Predicted Lending Shock on County Aggregate Outcomes

	Employment growth		Establishment growth		Wage Bill growth	Earnings per Worker growth
	CBP/QCEW	NETS	CBP/QCEW	NETS	CBP/QCEW	CBP/QCEW
	(1)	(2)	(3)	(4)	(5)	(6)
2009 shock * 2010	0.0006		0.0010		0.0019	0.0006
	(0.0008)		(0.0004)		(0.0009)	(0.0009)
2009 shock * 2009	0.0020	0.000	0.0012	0.0019	0.0037	0.0033
	(0.0010)	(0.001)	(0.0005)	(0.0010)	(0.0023)	(0.0025)
2008 shock * 2010	-0.0007		-0.0015		-0.0017	-0.0003
	(0.0008)		(0.0005)		(0.0012)	(0.0008)
2008 shock * 2009	-0.0006	0.0043	-0.0003	0.0052	0.0002	0.0015
	(0.0010)	(0.001)	(0.0006)	(0.0010)	(0.0014)	(0.0012)
2008 shock * 2008	0.0004	-0.0011	0.0002	0.0005	0.0025	0.0020
	(0.0008)	(0.0016)	(0.0004)	(0.0006)	(0.0011)	(0.0008)
φ_8: Effect of shocks in 2008	0.0004	-0.0011	0.0002	0.0005	0.0025	0.0020
	(0.0008)	(0.0016)	(0.0004)	(0.0006)	(0.0011)	(0.0008)
φ_9: Effect of shocks in 2009	0.0014	0.0042	0.0009	0.0070	0.0039	0.0047
	(0.0011)	(0.0011)	(0.0007)	(0.0012)	(0.0026)	(0.0028)
φ_{10}: Effect of shocks in 2010	-0.0001		-0.0005		0.0002	0.0003
	(0.0008)		(0.0005)		(0.0011)	(0.0010)
π_9: Cumulative effect through 2009	0.0018	0.0031	0.0012	0.0075	0.0064	0.0067
	(0.0015)	(0.0017)	(0.0010)	(0.0014)	(0.0032)	(0.0031)
π_{10}: Cumulative effect through 2010	0.0018		0.0007		0.0066	0.0070
	(0.0021)		(0.0014)		(0.0033)	(0.0027)
F-stat on shocks	0.3706	0.001	0.002	0.000	0.0161	0.0383
Observations	39012	36252	39012	36252	39012	39012

Notes: The entries come from the fitting of versions of equation (7). Standard errors clustered on county are in parentheses. An observation is a county by year cell. The sample spans 1998-2009. Shocks refer to predicted loan originations as specified in equation (4). All models include state by year fixed effects and the interaction of county characteristics with year dummies. County characteristics are 2006 values of log population density, log population, construction share, manufacturing share, and log per capita income. All main effects are included. See Table 4 or the text for the definitions of the φ and π parameters. In columns 2 and 4, employment and establishment growth rates are as defined in Table 5. For the remaining columns they are log changes. CBP/QCEW denotes that the growth rates are averages of growth rates in the County Business Patterns and the Quarterly Census of Employment and Wages. All models are weighted by the number of establishments in the county in 2006. See the text for further details.

Table 8: Effect of predicted lending shock on small business employment by year

	Log originations	Small standalone firm employment growth (NETS)	All Private employment (NETS)	All Private employment (CBP/QCEW)	Wage Bill (CBP/QCEW)
	(1)	(2)	(3)	(4)	(5)
Θ_1: Lending shock (t)	0.0498	-0.0008	0.0000	0.0003	0.0004
	(0.0029)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Θ_2: Lending shock (t-1)	0.0330	-0.0003	0.0010	0.0003	0.0002
	(0.0029)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Θ_3: Lending shock (t) *2008	0.0243	0.0026	-0.0004	0.0003	0.0019
	(0.0078)	(0.0009)	(0.0017)	(0.0009)	(0.0009)
Θ_4: Lending shock (t-1) *2009	0.0404	0.0044	0.0039	-0.0008	0.0015
	(0.0098)	(0.0011)	(0.0015)	(0.0010)	(0.0013)
Θ_5: Lending shock (t) *2009	0.0474	0.0019	0.0003	0.0020	0.0030
	(0.0082)	(0.0011)	(0.0013)	(0.0011)	(0.0027)
Θ_6: Lending shock (t-1) *2010	0.0881			0.0004	0.0005
	(0.0085)			(0.0008)	(0.0009)

Continued Below

Table 8 (Continued)

	Log originations	Small standalone firm employment growth (NETS)	All Private employment (NETS)	All Private employment (CBP/QCEW)	Wage Bill (CBP/QCEW)
	(1)	(2)	(3)	(4)	(5)
Effect of 2008 shock = $\Theta_1 + \Theta_2 + \Theta_3 + \Theta_4$	0.1475 (0.0134)	0.0059 (0.0015)	0.0045 (0.0017)	0.0001 (0.0015)	0.0041 (0.0016)
Effect of 2009 shock = $\Theta_1 + \Theta_2 + \Theta_5 + \Theta_6$	0.2183 (0.0142)			0.0029 (0.0015)	0.0041 (0.0021)
Excess effect of the 2008 shock beyond 'normal' times = $\Theta_3 + \Theta_4$	0.0647 (0.0147)	0.0070 (0.0016)	0.0035 (0.0017)	-0.0005 (0.0016)	0.0034 (0.0017)
Excess effect of the 2009 shock beyond `normal' times = $\Theta_5 + \Theta_6$	0.1355 (0.0150)			0.0024 (0.0016)	0.0035 (0.0023)
F-test for joint significance of interactions (p-value)	0.0000	0.00	0.01	0.503	0.097
Observations	30210	27189	27189	29976	29976

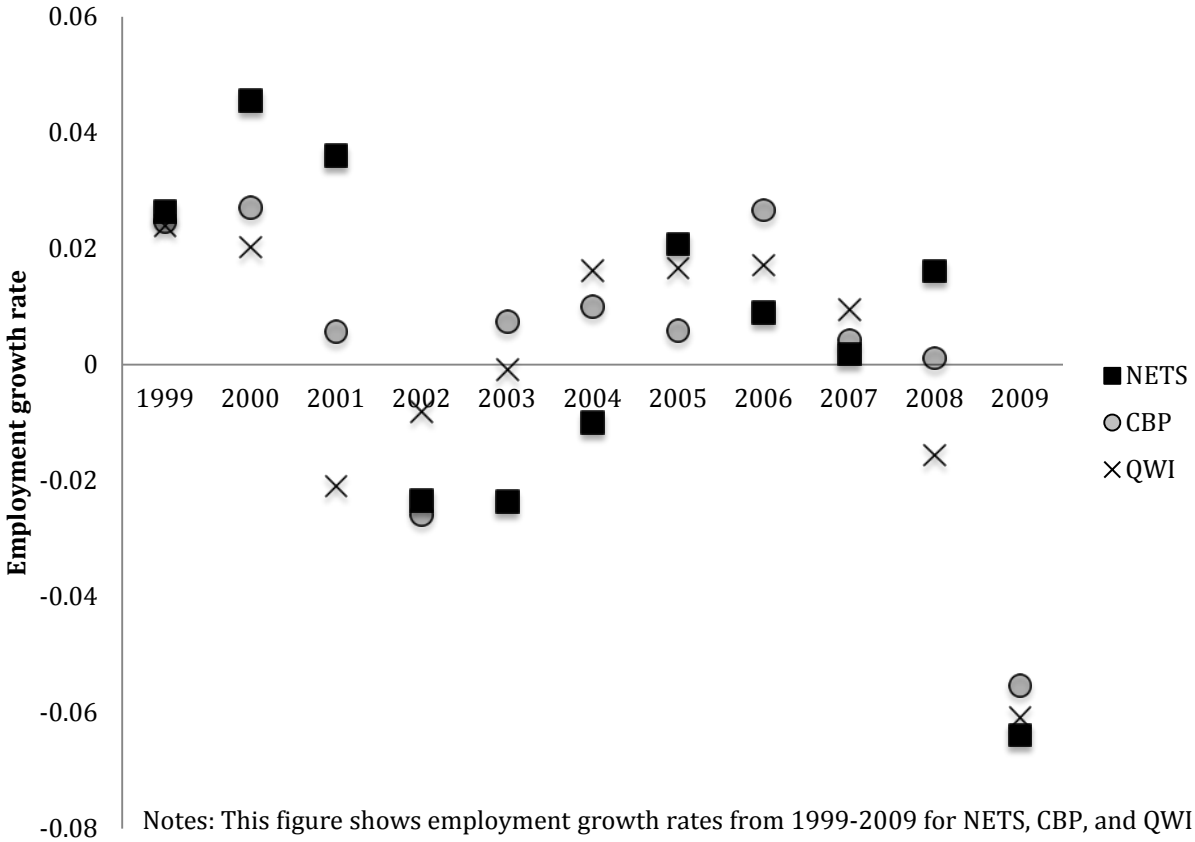
Notes: The entries come from the fitting of versions of equation (9). Standard errors clustered on county are in parentheses. An observation is a county by year cell. Shocks refer to predicted loan originations as specified in equation (4). All models control for state by year fixed effects and the interaction of county characteristics and year. County characteristics are log 2006 population density, log population, construction share, manufacturing share, and log per capita income. All main effects are included.

Table 9: Two Stage Least Squares Models of the Relationship Between Economic Activity and Small Business Loan Originations

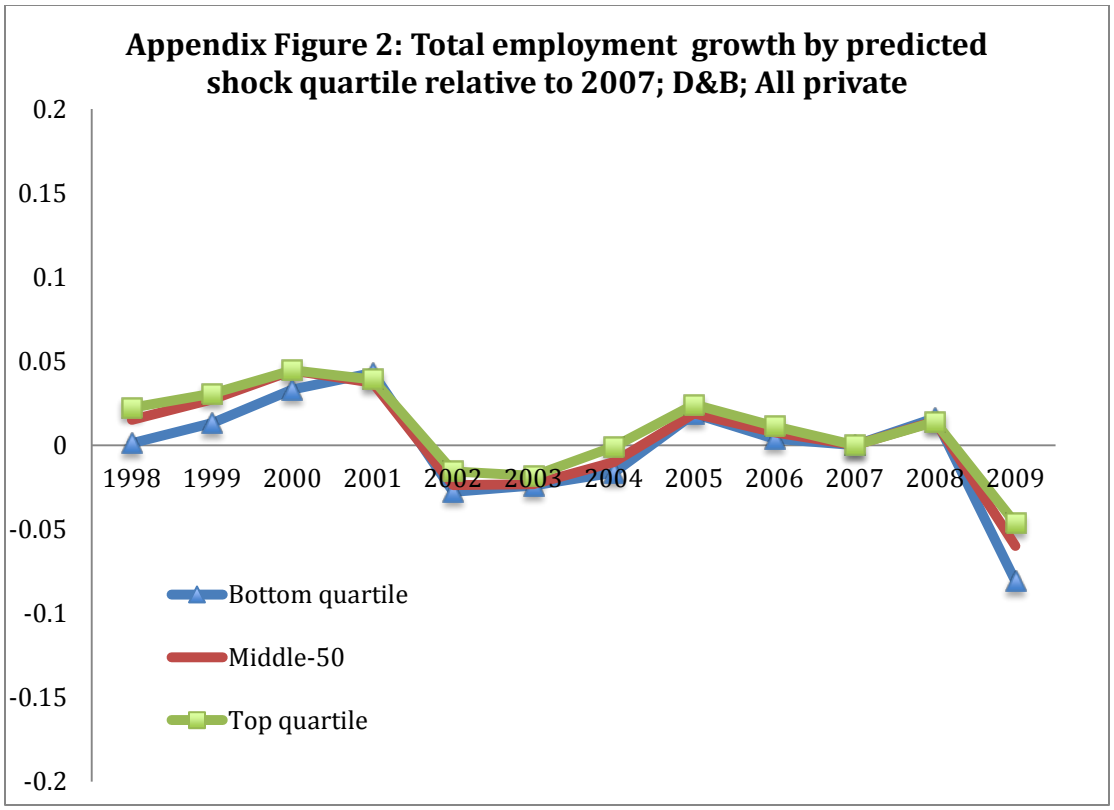
	Standalones-NETS		All private establishments CBP/QCEW/NETS		All private establishments CBP/QCEW
	Employment growth rate	Establishment growth rate	Employment growth rate	Establishment growth rate	Wage Bill growth rate
	(1)	(2)	(3)	(4)	(5)
log small loan originations (t)	0.017	0.023	0.006	0.010	0.033
	(0.007)	(0.008)	(0.007)	(0.004)	(0.016)
log small loan originations (t-1)	0.021	0.029	0.020	0.017	-0.028
	(0.014)	(0.011)	(0.012)	(0.005)	(0.016)
Estimated Upper Bound Impact of Credit Supply Reduction in 2008	0.004	0.005	0.001	0.002	0.007
Estimated Upper Bound Impact of Credit Supply Reduction in 2009	0.010	0.014	0.006	0.007	0.005
Angrist Pischke First-Stage F-stat (t)	89.96	89.96	90.17	90.17	52.42
Angrist Pischke First-Stage F-stat (t-1)	68.30	68.30	69.91	69.91	76.96
Hansen J statistic overidentification p-value	0.18	0.21	0.17	0.86	0.08
Observations	36252	36252	36060	36060	39012

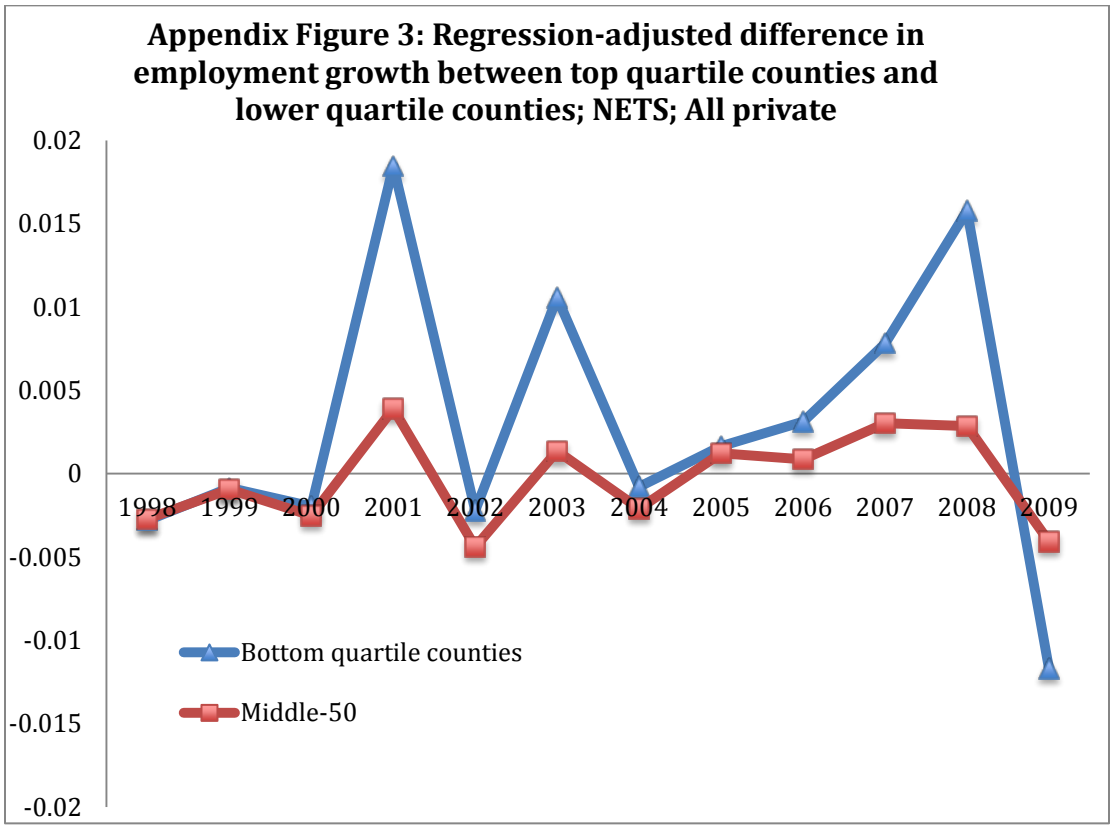
Notes: The entries come from the two stage least squares model described in Section VI of the paper. Standard errors clustered on county are in parentheses. An observation is a county by year cell. The sample spans 1998-2009. The dependent variables are noted in the column headings. In columns (3) and (4), the dependent variable is the average growth rate for a year and county across the CBP, QCEW, and NETS datasets. In column (5), the dependent variable is the average across the CBP and QCEW data sets. In all specifications the instruments are the 2008 predicted lending shock interacted with 2008 and 2009 year dummies, and the 2009 predicted lending shock interacted with the 2009 year dummy. All models include all main effects, state by year fixed-effects, and the standard set of county characteristic controls interacted with year dummies. Appendix Table 5 reports the results from the estimation of the corresponding OLS specifications with the identical samples.

Appendix Figure 1: Comparing employment growth rates by year for CBP, QWI, and NETS



Notes: This figure shows employment growth rates from 1999-2009 for NETS, CBP, and QWI


Appendix Figure 2: Total employment growth by predicted shock quartile relative to 2007; D&B; All private
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
Bottom quartile
Middle-50
Top quartile


Appendix Figure 3: Regression-adjusted difference in employment growth between top quartile counties and lower quartile counties; NETS; All private
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
Bottom quartile counties
Middle-50

Appendix Table 1

	ln(small business lending)
2009 shock * 2009	0.026 (0.026)
2008 shock * 2009	-0.024 (0.030)
2008 shock * 2008	-0.055 (0.031)
Observations	29284

Notes: In this table we test whether areas with larger credit shocks experienced increased lending of banks not covered by the CRA. The unit of analysis is commercial banks that are below the CRA asset threshold. The dependent variable is small loan balances from FDIC Call reports. Standard errors clustered on county. See the text for further details.

Appendix Table 2: Comparing NETS to other data sources of employment at the county and state-level

Panel A: Correlations with county-year data, 2005-2009

	ln(emp) QWI	ln(emp) QCEW	ln(emp) CBP	ln(emp) NETS
ln(emp) QWI	1			
ln(emp) QCEW	0.99	1		
ln(emp) CBP	0.99	0.99	1	
ln(emp) NETS	0.99	0.99	0.99	1

Correlations in yearly change with county-year data, 2005-2009

	Δ ln(emp) QWI	Δ ln(emp) QCEW	Δ ln(emp) CBP	Δ ln(emp) NETS
Δ ln(emp) QWI	1			
Δ ln(emp) QCEW	0.74	1		
Δ ln(emp) CBP	0.58	0.70	1	
Δ ln(emp) NETS	0.47	0.52	0.43	1

Panel B: Size 1-19 establishments; 1997-2009; State x year observations

	Net job creation rate BDS
Net job creation rate NETS	0.53

Panel C: Size 1-19 establishments; 2005-2009; State x year observations

	Net job creation rate BDS
Net job creation rate NETS	0.72

Appendix Table 3: Relationship between quartiles of predicted lending shock and ln(loan originations)

	(1)	(2)
Bottom quartile * 2010	-0.201	-0.301
	(0.045)	(0.028)
Bottom quartile * 2009	-0.249	-0.347
	(0.043)	(0.025)
Bottom quartile * 2008	-0.011	-0.150
	(0.032)	(0.023)
Interquartile * 2010	-0.045	-0.173
	(0.022)	(0.019)
Interquartile * 2009	-0.089	-0.206
	(0.023)	(0.018)
Interquartile * 2008	0.008	-0.117
	(0.022)	(0.016)
p-value on shock interactions	0.000	0.000
Observations	40404	39273
County characteristics * year dummy		x
State * year effects		x

Notes: The entries come from the fitting of versions of equation (7). Standard errors clustered on county in parentheses. An observation is a county by year cell. Quartiles refer to the predicted lending shock measure defined in equation (4). The sample spans 1998-2010. County characteristics are log 2006 population density, log population, construction share, manufacturing share, and log per capita income. All main effects are included. See the text for further details.

Appendix Table 4: Effect of Predicted Lending Shock on Employment and Establishment Growth Rates by Size of Firm; NETS database; With controls for housing price appreciation 2002-2006

	Employment growth rate	Employment growth rate	Establishment growth rate	Establishment growth rate
	1	2	3	4
2009 shock * 2009	0.000	-0.001	0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
2008 shock * 2009	0.008	0.007	0.011	0.010
	(0.002)	(0.002)	(0.003)	(0.003)
2008 shock * 2008	0.002	0.001	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Effect of shocks in 2008	0.002	0.001	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Effect of Shocks in 2009	0.009	0.007	0.012	0.009
	(0.003)	(0.003)	(0.003)	(0.003)
Cumulative effect of shocks through 2009	0.011	0.008	0.015	0.010
	(0.003)	(0.003)	(0.004)	(0.003)
p-value on shock interactions	0.00	0.01	0.00	0.00
Observations	6816	6816	6816	6816
Lagged county characteristics * year dummies	X	X	X	X
Sample limited to counties with home price data	X	X	X	X
Housing price appreciation 2002-2006 * year dummies		X		X
State * year effects	X	X	X	X

Notes: The entries come from the fitting of versions of equation (7) on data from the NETS database. Standard errors clustered on county are in parentheses. An observation is a county by year. In columns (1) and (3) the sample is limited to counties that have home price data. See notes to Table 5 for variable definitions. The sample spans 1998-2009. The sample corresponds to small standalone establishments, which are defined as less than 20 employees. County characteristics are log 2006 population density, log population, construction share, manufacturing share, and log per capita income. All main effects are included. See the text for further details.

Appendix Table 5: OLS Models of the Relationship Between Economic Activity and Small Business Loan Originations

	Standalones-NETS		All private establishments - CBP/QCEW/NETS		All private establishments - CBP/QCEW
	Employment growth rate	Establishment growth rate	Employment growth rate	Establishment growth rate	Wage Bill growth rate
	(1)	(2)	(3)	(4)	(5)
log small loan originations (t)	0.001	-0.001	0.000	0.0008	0.004
	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)
log small loan originations (t-1)	-0.004	-0.005	-0.001	-0.003	-0.005
	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)
Observations	36252	36252	36060	36060	39012

Notes: The entries come from the least squares versions of the equations used to generate the results in Table 9. Standard errors clustered on county are in parentheses. An observation is a county by year cell. The sample spans 1998-2009. The dependent variables are noted in the column headings. In columns (3) and (4), the dependent variable is the average growth rate for a year and county across the CBP, QCEW, and NETS datasets. In column (5), the dependent variable is the average across the CBP and QCEW data sets. All models include all main effects, state by year fixed-effects, and the standard set of county characteristic controls interacted with year dummies. Table 9 reports the results from the estimation of the corresponding OLS specifications with the identical samples.